Analysis and Evaluation of the Impacts of Predictive Analytics on Production System Performances in the Semiconductor Industry.

Simon J. Preis

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Abstract

Problem Statement: Predictive Analytics (PA) may effectively support semiconductor industry (SI) companies in order to manage the special challenges in SI value chains. To discover the implications of PA, the realistic benefits as well as its limitations of its application to semiconductor manufacturing, it is necessary to assess in which ways the application of PA affects the production system (PS) performances. However, based on the literature survey, the influences of PA on the various performance characteristics of an SI PS are not as clear as expected for the efficiently operative application. Besides, the existing performance models are not effective to predict the impacts of PA on the SI PS performances. Therefore, the overall aim of this thesis is to analyse and evaluate the impacts of PA on the SI PS performances and to identify under which conditions a PA application would generate the most significant performance improvements. The focus of this thesis is predictive maintenance (PdM).

Research Methodology: Based on a post-positivist philosophy, the thesis applies a deductive research approach using mixed-methods for data collection. The research design has the following stages: (1) theory, (2) hypothesis, (3) state of research, (4) case study and (5) verification.

Main Achievements: (1) The systematic literature review is carried out to identify the gaps of the existing research and based on these findings, a conceptual framework is proposed and developed. (2) The existing performance models are analysed and evaluated against their applicability to this study. (3) A causal loop model for SI PS is generated based on the assessment of experts with industrial engineering and equipment maintenance expertise. (4) An expert system is developed and evaluated in order to investigate transitive and contradictory effects of PdM on SI PS performances. (5) A simulation model is developed and validated for investigating the strengths and limitations of PdM regarding SI PS performances under different circumstances.

Results: The results of the logical inference study show that PdM has 34 positive effects as well as 4 contradictory effects on SI PS performance characteristics. Based on the various simulation experiments, it has been found that (1) ’Mean Time to Repair’ decreases only if PdM supports proportionate reduction of failures and repair times. (2) Logistics performance improves only if the underlying workcenter is limited in capacity or the four partners are non-synchronous. (3) PdM supports optimal cost decreases for workcenters where the degree of exhausting wear limits can be most effectively improved and (4) the degree of yield improvement gained by PdM is dependent on the operation scrap rate. However, (5) if a workcenter has overcapacity, PdM will potentially worsen PS performances, even if the particular workcenter performance can be improved. These new insights advance existing knowledge in production managements when adopting predictive technologies at SI PS in order to improve PS performances. The findings above enable SI practitioners to justify a

PdM investment and to select suitable workcenters in order to improve SI PS performances by applying the proposed PdM.

Contributions: The main contributions of this PhD project can be divided into practical application and theoretical work.

The contributions from the theoretical perspective are:

1) The critical review and evaluation of the state of the research for PA in the context of semiconductor manufacturing and the models for predicting and evaluating SI PS performances.
2) A new framework for investigating the implications of PA on the challenges such as gaining high utilizations and controlling the variability in production processes in SI value chains.
3) The new knowledge about transitive and contradictory effects of PdM on SI PS performances, which indicates that PdM can be used to improve PS performances beyond a single machine.
4) The new knowledge about strengths and limitations of PdM in order to improve SI PS performances under particular circumstances.

The contributions from the practical application perspective are:

1) A practical method for identifying workcenters where PdM delivers the most significant benefits for SI PS performances.
2) An expert system that provides a comprehensive knowledge base about causes and effects within SI PS in order to justify a PdM investment.
3) A concise review of important PA applications, their capabilities for the wafer fabrication and the most suited PA methods. These findings can be adopted by SI practitioners.

Limitations: Due to the resource and time constraints of this PhD project, this thesis is only focused on PdM, though the proposed framework, tools and method are generic and valid for other PA applications as well. In addition, the thesis concentrates on the frontend part of the SI value chain.

Author’s declaration

I declare that the work in this thesis was carried out in accordance with the regulations of the University of Gloucestershire and is original except where indicated by specific reference in the text. No part of the thesis has been submitted as part of any other academic award. The thesis has not been presented to any other education institution in the United Kingdom or overseas. Any views expressed in the thesis are those of the author and in no way represent those of the University.

Signed …………………………………….. Date ……..28 July 2020..……

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List of Abbreviations and Acronyms

A

Alpha / α · *Variability*

A_m · *Machine availability*

ANN · *Artificial neural network*

$\boldsymbol{A_{PS}}$ · *Production system availability*

B

BI · *Business intelligence*

C

CIM · *Computer integrated manufacturing*

CLM · *Causal loop model*

CT · *Cycle time*

D

DGR · *Daily going rate*

DM · *Data mining*

E

EI · *Equipment integration*

EM · *Equipment maintenance*

EoL · *End-of-line*

ERP · *Enterprise resource planning*

F

FF · *Flow factor*

FoL · *Front-of-line*

FOL · *First-order logic*

G

GR · *Going rate*

I

IDM · *Integrated device manufacturers*

IP · *Intellectual property*

IT · *Information technology*

K

KPI · *Key performance indicator*

L

LED · *Light-emitting diodes*

M

MDM · *Master data management*

MTBA · *Mean time between assists*

MTOL · *Mean time offline*

MTTF · *Mean time to failure*

MTTR · *Mean time to repair*

O

OC · *Operating curve*

OE · *Operational efficiency*

OEE · *Overall equipment efficiency or effectiveness*

OPC · *Operations planning and controlling*

OSAT · *Outsourced semiconductor assembly and test*

OWL · *Web ontology language*

P

PA · *Predictive analytics*

PdM · *Predictive maintenance*

PdMSM · *Predictive maintenance simulation model*

PM · *Performance model*

PMS · *Performance measurement system*

PPES · *Production performance expert system*

PS · *Production system*

Q

QE · *Quality efficiency*

R

RE · *Rate efficiency*

RO · *Research objective*

RPT · *Raw process time*

RQ · *Research question*

S

SCM · *Supply chain management*

SD · *System Dynamics*

SEMI · *Semiconductor equipment and materials international*

SFC · *Shop floor control*

SI · *Semiconductor industry*

SM · *Smart manufacturing*

SVM · *Support vector machine*

SWRL · *Semantic web rule Languagel*

U

U · *Utilisation*

UD · *Unscheduled down*

W

WIP · *Work in progress*

Chapter 1 Introduction

1.1 Project Background

The semiconductor industry (SI) provides important and indispensable components for current applications in all areas of life and business. These applications include but are not limited to automotive (e.g., distance radars in cars), communications (e.g., GPS chips), industrial applications (e.g., embedded systems in production equipment) as well as consumer electronics (e.g., modems for smart phones). The growing importance of semiconductor devices is also reflected by the economic profit of the whole industry: SI generated $97 billion in economic profit in 2017, which is more than a threefold increase compared to 2013 (Jong and Srivastava, 2019).

Because the design and fabrication of semiconductor devices is a high-technology process, the customer businesses are diverse, and the market is volatile, SI value chains face special challenges compared to other industries. These challenges can be summarized as follows:

1) SI distributes various types of products to customers that can be categorized, for instance, as memory, micro-component, and optoelectronic devices. In addition, each category contains multiple sub-types that may differ significantly in production and application, e.g. light-emitting diodes versus lasers, which are both categorized as optoelectronics but serve disjoint applications.
2) The industry consists of several types of business models such as integrated device manufacturer, foundry and IP licensing. In addition, an SI company is not limited to only one business model and may operate with different models simultaneously.
3) To manufacture a finished good in SI, a chip usually runs through the ‘frontend’ and the ‘backend’ stage of the value chain. This process typically involves multiple sites and countries across the globe. For instance, global market leader Intel (2011) operates most of its ‘frontend’ facilities from USA, whereas most of the ‘backend’ facilities are located in Asia – and none of them in USA.

4) SI belongs to the most research- and development (RnD)-intensive industries in the world with industry-wide investment rates ranging between 15 and 20 % of sales. Due to comparatively short product lifecycles and continuous product and process improvements, it is required to integrate RnD tasks into the primary value chain in order to reduce time-to-market and improve product yields. This type of organization is reflected, for instance, by Alam et al. (2020). Designing and managing a production system (PS) that is both enough flexible to serve RnD requirements and sufficiently stable to run a mass production is a challenging conflict of goals.
5) Especially the manufacturing parts of the SI value chain face various challenges, which can be categorized by product management, data and IT, engineering, and others. Typical challenges are the variability in production processes, unpredictable product differentiations and high testing efforts. However, the largest number of challenges is associated to logistics. Such challenges include the importance of capacity, the inverted bill of materials and the conflict of goals between short runs and high utilization.

Since SI produces masses of data during the manufacturing process (e.g. equipment telemetric data, process data, and wafer probing), it can be assumed that data-driven approaches may support managers and engineers to overcome these challenges. In fact, a growing attention on predictive analytics (PA) can be found in SI and particularly in semiconductor manufacturing. This increasing importance correlates to other trends in manufacturing such as ‘smart factory’, the German ‘Industry 4.0’ and ‘cyber physical production system’. However, the most important drivers might be the rapidly increased technical capabilities of both to store and process the masses of data, which is usually summarized as ‘Big Data’.

To approach the question in which way PA may help to overcome the mentioned challenges, and subsequently, generate benefits for a company, an appropriate perspective must be identified. The thesis identified three perspectives: (1) PA in general, (2) single PA methods, and (3) particular PA applications. Since PA is not commonly defined in literature and its methods and possible applications are extensive, it is not seen as realistic that any benefit could be calculated on this high level. The second perspective would evaluate benefits of single predictive techniques such as artificial neural networks and support vector machines. However, the review of previous studies indicates that one does not start a PA project by selecting a technique, but the PA project selects an appropriate technique in a later stage based on its validated prediction score. The source data, the type of data preparation and the actual prediction goal can influence the score. A general benefit cannot be stated for a PA technique, because it is not determinable whether it can be applied at all without knowing the actual environment and goal. Hence, it is not seen as reasonable to evaluate benefits for a technique by itself. Instead, it is proposed to focus on the third perspective: PA applications that are crucial for SI value chains in order to discover which process improvements they would generate, which specific challenges they would master and which types of benefits would arise. To narrow down the scope of this thesis, only the wafer fabrication (also called ‘frontend’) part of the SI value chain is considered and possible benefits that are generated with regards to the PS performance by introducing a selected PA application to a frontend facility are evaluated. However, the literature review indicates an inconsistent use of ‘performance’ and related terms. Therefore, this thesis considers PS performance to be evaluated from four perspectives: (1) logistics, (2) quality, (3) engineering, and (4) maintenance. These perspectives are related to the manufacturing-related challenges in SI value chains that could be mastered by PA as proposed by the conceptual framework in Chapter 2. It is implied that the actual value of PS key performance indictors (KPIs) reflect the ability of a SI company to master particular challenges in SI value chains. If PA is capable of improving a KPI (e.g. equipment utilization), it is concluded that PA supports to overcome the underlying challenge (e.g., high utilization is required due to cost-intensive equipment).

From the literature review, the following PA applications are found to be relevant for SI frontend PS: (1) predictive maintenance (PdM), (2) smart manufacturing, (3) predictive process control, (4) predictive quality, and (5) predictive dispatching and scheduling. Some of these applications show overlapping goals. For instance, PdM aims to predict machine faults, which is also a goal of ‘fault prediction’ that belongs to process control. Possible demarcations will be discussed and proposed in Section 2.5 in order to sharpen the definition of each application. Apart from single overlaps, the applications and associated goals differ significantly. In addition, each of these applications refers to a different group of experts such as industrial engineers, process engineers or quality engineers. In order to evaluate benefits of PA applications, each group of stakeholders must be interviewed to collect, analyse and evaluate the logical dependencies within the PS. Limitations in time and resource cause that no such method can be developed as part of a doctoral thesis that considers all perspectives in order to evaluate all types of benefits simultaneously. Hence, it is proposed to focus only on one selected PA application to demonstrate the new approach. Further research can be conducted beyond the thesis to extend this approach by adding further expert perspectives and PA applications. By analysing SI-related articles that are employed with these applications, PdM appears to be the most important solution at this time. Further increase is forecasted in the global PdM market beyond SI over the next years, which underpins that the importance of this application is still growing. Based on this finding, PdM is selected as PA application under study.

To prove the importance and originality of this project, various articles were reviewed and existing frameworks that are employed with benefits of PA were analysed and evaluated. It turned out, that none of the proposed frameworks is suited to this research project. For instance, the majority of literature is not focussed on SI, and therefore, the industry-specific challenges are not considered. In addition, existing and published SI-related performance models are found to be not capable of supporting the aim of this thesis. These findings indicate a gap in the literature that is addressed by this thesis.

1.2 Motivation

Observations in real semiconductor companies suggest that many benefit estimations for IT investments in the manufacturing area are not based on realistic calculations, since the underlying environment – the present PS – is usually neither analysed nor evaluated in an objective way that includes transitive or dynamic effects. Especially for data-centric solutions, it is difficult to calculate a realistic benefit. The substitution of a human by a robot can be evaluated based on comprehensible facts, e.g., the increased number of handling activities per hour, the increased accuracy, and therefore, reduced handling errors and increased yield. By adding monetary characteristics such as the increased chip output that improves the revenue, the profitability of a robot can be proved. Data-centric solutions such as data quality tools or PA applications, however, cannot be evaluated in an equivalent way – at least in the area of semiconductor manufacturing. Technology companies such as Facebook, Google and Amazon demonstrate that their market value is directly related to the value of their data and how they use this data. Data can create new data that may lead to new business opportunities and also advanced ways to use the data (Press, 2018). By contrast, the market value of semiconductor companies is strongly related to their intellectual property for chip design or advanced manufacturing technologies (see 2.2). Admittedly, data is crucial to understand failure patterns and to improve product yields. Masses of data are produced during the manufacturing process that can be used to analyse deviations in single process steps. However, it is not clear to state in which way a semiconductor company would gain profit, if the data quality would improve or PA applications would be applied. Typical issues are that the potential positive effects of such data-centric solutions are either delayed or appear at other positions in the value chain. The knowledge about these effects is important, because the implementation of a predictive solution requires considerable expenses such as human efforts and technology investments (see 5.2.4). For instance, it is assumed in literature that PdM is able to reduce unscheduled downtimes of a machine. The development of a machine-specific PdM solution is expensive, even for particular components of the machine. This leads to the question: which benefits are created when the unscheduled downtime of this particular machine is reduced and are the required efforts justified?

The motivation for this research is, therefore, to find a way to analyse and evaluate the implications of PA under consideration of time and transitive effects. To narrow down the bandwidth of transitivity, it shall be discovered in which way PA improves the PS performance in SI. These new insights will gain transparency for future PA technology investments in the SI manufacturing area.

1.3 Research Questions, Overall Aim and Objectives

As suggested by the previous section, the aim of this research is to analyse and evaluate the impacts of predictive analytics on the production system performance in SI. The conceptual framework for this thesis presents different types of PA applications that are relevant to SI manufacturing and that could be applied to overcome specific challenges in SI value chains (see 2.6). Each of those applications has different majors and goals, and hence, requires a different setup in terms of source data, business processes, IT systems and participating business experts. Due to this heterogeneity in setups and goals, it is believed that an objective and reliable evaluation cannot consider all types of PA applications at once. In addition, the efforts for collection and evaluation of primary data for all types of PA applications would exceed the capacity of a doctoral thesis. Therefore, this thesis selects one particular PA application in order to discover its various benefits and other effects regarding production performance. Based on the results of the literature review (see Chapter 2), the thesis selects PdM as focus application. The growing and present number of articles concerned with PdM in SI indicates an overriding relevance of this application. In addition, other PA applications show noteworthy overlaps with the setup of PdM. Therefore, it is expected that downstream projects can adopt and extend the tools and methodology developed by this thesis to examine further PA applications.

This research intends to find a method that is capable of analysing and evaluating benefits for PS performance when applying PdM. Possibly, performance models exist that can be applied to this study. For this purpose, research articles must be reviewed that are employed with performance models in SI manufacturing. This assumption leads to the first research question (RQ):

1) What is the current state in research on simulating and evaluating the production system performance in SI?

As discussed in 1.2, it is supposed that benefits of PA applications are not limited to the object that is under predictive study, e.g., a particular machine. The thesis aims to identify the transitive effects of PdM on the SI PS performance. Prior to discover transitive effects, the performance-critical characteristics of an SI PS must be identified. Then, the direct influences and causal dependencies between these characteristics and PdM must be identified. The underlying RQ is:

2) Which are the performance-critical characteristics of an SI PS, how are they causally related, and how are they affected by application of PdM?

Once the direct effects are captured and modelled, the transitive effects of PdM on the SI PS can be discovered. It is believed that transitive influences between model elements are not only straight positive or negative but also contradictory in some situations. To confirm this hypothesis qualitatively through logical inference, the thesis will develop and propose a knowledge-based system, which is called production performance expert system (PPES). The PPES shall be adoptable by researchers and managers in the area of SI manufacturing to discover the direct and transitive impacts of PdM on SI PS. The according RQ is:

3) Can a knowledge-based system be developed to compute the transitive or even contradictory impacts of PdM on SI PS performance qualitatively?

Another hypothesis in this research is that the actual impacts of PdM on the SI PS performance are not static but dependent on particular workcenters, operations, and the product line itself. Furthermore, it is assumed that there are scenarios where PdM would even decrease the overall PS performance. To confirm this hypothesis quantitatively, a model for dynamic simulation of SI PS behaviours will be developed. It shall be configurable to execute simulations under consideration of different workcenters, operations and production line characteristics. The results will be used to confirm (or reject) that the impacts of PdM on the SI PS performance differ and may also be negative. In addition, the model can be applied to real SI companies to identify workcenters that increase the SI PS performance at most when applying PdM. These activities are addressed by the final RQ:

4) Can a simulation model be developed to quantify the impacts of PdM on SI PS performance over time under consideration of particular workcenters, operations and production line characteristics?

The overall aim is to prove the benefits (and disadvantages) of PA in the context of SI PS performance qualitatively and to identify parts of the SI PS where a PA application would generate the most significant performance improvements. As discussed in 1.1, the approach to achieve this overall aim will be demonstrated by PdM as selected PA application.

To achieve this overall aim, the following research objectives (ROs) are set out:

1) To review and evaluate existing models for simulating and evaluating the PS performance in SI.
2) To identify and analyse performance-critical characteristics of an SI PS and in which way they are causally dependent and affected by application of PdM.
3) To propose, design, develop, and validate an expert system for SIPSs in order to compute the transitive or contradictory impacts of PdM on SI PS performance qualitatively.
4) To propose, design, develop, and validate a dynamic simulation model for quantitative analysis and evaluation of the impacts of PdM on SIPSs over time under consideration of particular workcenters, operations, and production line characteristics.

1.4 Contributions to the New Knowledge Generation

This research will advance existing knowledge in production management when adopting predictive technologies at SI PS. Since the research project is strongly related to practical issues in SI, its contributions can be divided into practical application and theoretical work. The main contributions from theoretical perspective will be as follows:

1) The thesis will contribute the reviewed state of research for PMs in SI including a classification and evaluation of existing PMs, which will support other researchers in similar projects.
2) The thesis will identify and review current research activities in the area of PA and especially in context of semiconductor manufacturing. The detected findings will include inconsistencies and gaps in literature beyond the scope of this thesis. Other projects may build up on these findings to conduct further research.
3) The thesis will propose a new framework that discovers in which way PA may be applied in order to overcome challenges in SI value chains. This framework can be adopted by other research projects in the area of PA and SI.
4) The thesis will identify, analyse and evaluate direct, transitive and even contradictory effects that may occur when PdM is applied to SI PS based on expert assessment and logical inference. In addition, the underlying expert system can be extended to further PA applications, which supports further research in this area.
5) The thesis will identify, analyse and evaluate under which particular circumstances PdM may generate the most significant performance benefits to SI PS logistics and when it would even decrease the performance.

Based on these contributions, researchers will be able to conduct further studies to understand the transitive and contradictory impacts as well as environment-specific dynamic effects of PA on SI PS performance. From practical perspective, the main contributions will be as follows:

1) The thesis will propose a new method to identify workcenters where PdM would gain the most significant benefits for SI PS performance. This method supports production managers and engineers to prioritize and select appropriate workcenters at their facilities that justify the required efforts of implementing a PdM solution.
2) The thesis will provide an expert system that can be queried in order to retrieve logical dependencies between SI PS participants. This comprehensive knowledgebase was not existing prior to this study and supports production managers and engineers to gain deeper

understanding of causes and effects within SI PS, especially when adopting PdM.

3) The thesis will identify and discuss the most relevant PA applications and capabilities for SI frontend manufacturing. The findings will support IT and production managers in defining PA strategies and setting up appropriate PA projects for their company. In addition, PA techniques that have been verified in literature to gain most promising results for a particular PA application will be highlighted.

Generally, the tools and the particular results for PdM will support SI production managers in adopting predictive technologies to overcome logistics challenges in wafer fabrication.

1.5 Thesis Structure

The thesis consists of nine chapters that are shown in Figure 1-1.

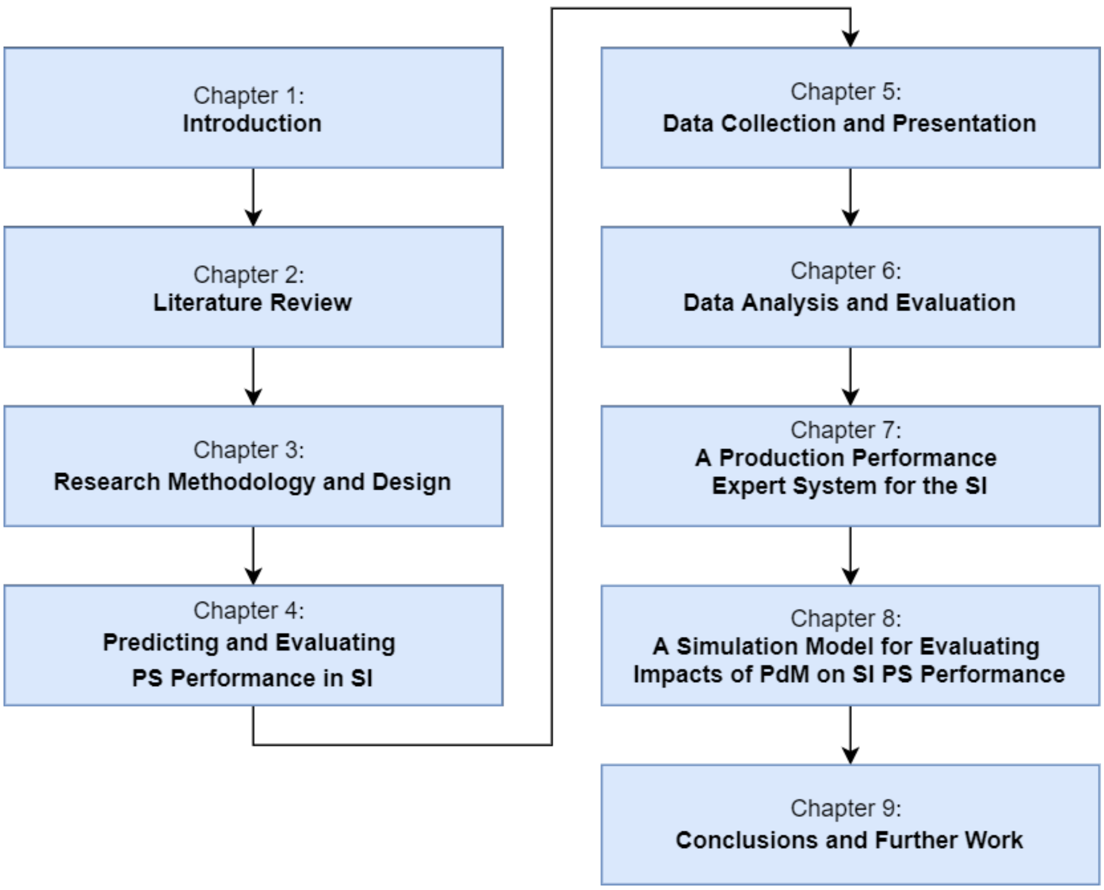


Figure 1-1: Thesis Structure

Following the introduction chapter, Chapter 2 presents the review of literature that is related to this thesis. The areas of literature are divided into SI, PA in general, PA methods and PA applications that are relevant to semiconductor manufacturing. The chapter concludes with a conceptual framework, which underpins the hypotheses and research questions.

The research methodology and design for the thesis are presented in Chapter 3. It starts with the discussion and definition of an appropriate research methodology for this project, which includes among others the research philosophy, research approach and techniques for data collection. Hereafter, specific research methods and software tools are presented that are applied to this thesis in order to analyse data and to develop an expert system and a dynamic simulation model. The chapter finally presents a research design for this thesis and discusses ethical issues.

Chapter 4 introduces crucial terms and formulas to evaluate SI PS performance and presents the review of existing PMs in SI. At first, the term ‘production system’ is narrowed down and particularly defined for this project. After that, the evaluation of PS performance is discussed and defined for this thesis followed by the presentation of relevant KPIs of SI PS. Finally, the chapter reviews published PMs that are capable of predicting the development of KPIs in SI PS to verify if any of them could be applied to this study. The result of this verification solves RO 1.

The case study for primary data collection is conducted at a real SI company and is discussed in Chapter 5. The chapter introduces the case study company and the aims of the data collection. Then, the preparation of the data collection is discussed followed by the actual data collection. In addition, secondary data regarding the manufacturing process and data from IT systems is presented.

Chapter 6 presents the analysis and evaluation of the raw data that was gathered through the case study. At first, it presents the analysis and evaluation of the industrial engineering (IE)-specific data followed by the equipment maintenance (EM) specific data. Then, the expectations regarding PdM from both groups of experts are analysed and assessed. Finally, the EM- and IE-specific results are consolidated into a common causal loop model (CLM) and the direct logical relationships are evaluated in order to solve RO 2.

The development and evaluation of the knowledge-based PPES in order to solve RO 3 is discussed in Chapter 7. After defining the scope and boundaries of the expert system, the term transformation into ontology concepts is discussed. Hereafter, a class hierarchy is developed for the ontology followed by the object properties that associate various concepts. To finalize the PPES development, the formulation of first-order logical rules is presented. The chapter concludes with an analysis and evaluation of the PPES, which includes the implication of new knowledge.

In Chapter 8, the development and evaluation of a dynamic simulation model is presented in order to solve RO 4. The chapter begins with the proposition of a method to apply the model to a practical use case. Then, the scope and considerations of the simulation model are presented followed by the discussion about transforming terms into System Dynamics (SD) variables. Afterwards, the development of the model is presented that consists of multiple sub-models and a specific user interface. To verify the model, various test cases are applied and discussed in a further section. Finally, the chapter presents the new knowledge that was gained from experiments based on the simulation model.

Finally, Chapter 9 will conclude the thesis by presenting the main achievements and the contributions to the new knowledge generation. It further discusses the limitations of this thesis and proposes further work that can build on this project.

Chapter 2 Literature Review

2.1 Introduction

This chapter firstly presents the literature review in the following areas:

- SI and optoelectronics in particular
- Definition and overview of predictive analytics
- Methods for predictive analytics
- Predictive analytics applications in semiconductor manufacturing

Based on the review, a conceptual framework will be proposed.

2.2 The Semiconductor Industry

2.2.1 History and Industry Overview

The event and point in time when the history of SI begins is not clearly defined in literature. A comprehensive study from Łukasiak and Jakubowski (2010) pointed out that the semiconductor history goes back to the first observation of a semiconductor effect in 1833 by Michael Faraday. Hitachi (2015) declared the invention of the rectifier, which is an AC-DC converter, in 1874 as the earliest historical event. According to Tel (2018), the development of SI began in 1904 with the invention of the two-electrode vacuum tube rectifier. Ward (2014) located the beginning of semiconductor history in 1906 when a patent was granted for the construction and operation of the 'cat whisker' crystal detector. More specifically, Malerba (1985) suggested that the SI was initiated in 1947 as Bell Laboratories had discovered the transistor. This historical inaccuracy in literature must be refined. For this purpose, it is suggested to differentiate the historical perspective between the semiconductor technology itself, semiconductor-based applications, as well as the industrial development of the semiconductor market that is established today.

- The **technological history** includes all inventions that build on each other to make use of the semiconductor capabilities. Based on Faraday's experiments, this may include the revelation of the photovoltaic effect in 1839, the discovery of the photoconductivity in 1879, and others (Łukasiak and Jakubowski, 2010).

- The beginning of the **application-oriented history** correlates to the invention of crystal detectors. According to the Computer History Museum (2016a), the first patent for a point-contact semiconductor rectifier for detecting radio signals was granted to Jagadish Chandra Bose in 1901. However, it was emphasized that the 'cat whisker' crystal detector from 1906 was the first product based on semiconductor technology that gained economic profit.
- As for the **industrial history**, Loeffler (2019) and Gargini (2017) agreed that it started with the foundation of the Shockley Semiconductor Laboratory in 1955. Several employees of this company later founded their own successful SI companies such as Fairchild, Intel and AMD (Computer History Museum, 2016b).

Since the 1970s, the semiconductor unit shipment has continued to grow almost year-on-year as shown in Figure 2-1 (Matas, 2019).The number of units includes integrated circuits and optoelectronics, sensors, and discrete devices. The compound annual growth rate is 9.1% from 1979 until 2018. This significant level of growth must be emphasized taking into account the volatile market situation that is typical in SI. The largest annual increase in unit growth was 34% in 1984, whereas the greatest decline was 19% in 2001, as a result of the dot-com bust (Matas, 2019).

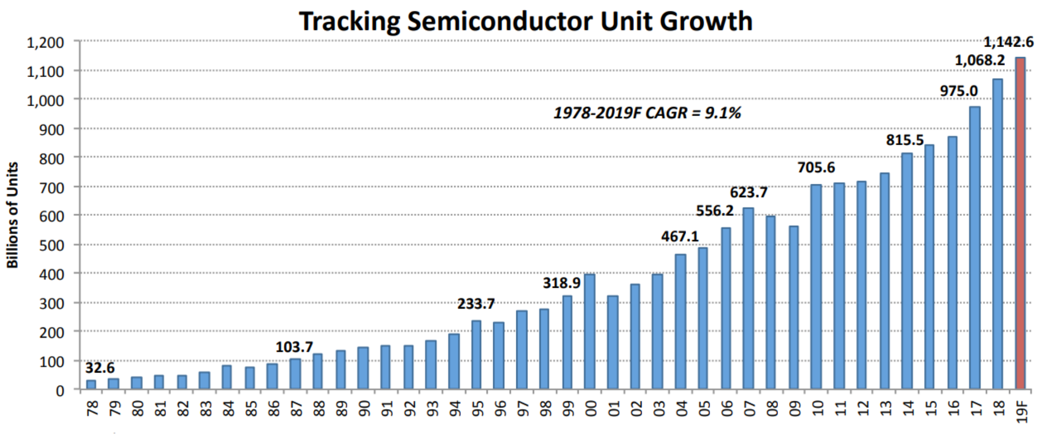


Figure 2-1: Semiconductor Unit Growth since 1978 (Matas, 2019, p. 1)

In addition, from a value-creation perspective, the SI has improved significantly over recent years compared to other industries. Particularly in 2017, SI generated $97 billion in economic profit, which is more than a threefold increase compared to 2013 (Jong and Srivastava, 2019).

There are various business models with different focuses and strengths in SI:

- Integrated device manufacturers (IDM)
- Foundries
- Fabless Companies
- Outsourced semiconductor assembly and test (OSAT)
- Intellectual property (IP) licensing
- Capital equipment

The first-generation SI companies, such as Intel and AMD, were capable of both designing and manufacturing semiconductor devices. These companies owned the complete value chain and are called IDM. In the late 1980s, another business model was developed with a combination of foundry companies and fabless companies. Semiconductor foundries are companies that fabricate the designs of other companies, whereas fabless companies specialize in the design, and outsource the fabrication of the devices. The evolution of this business model has been a driver for the global supply networks that are typical in SI. Many foundries were established in Asia, whereas many fabless companies were founded in the United States (Saito, 2009).

Changing the business model can also be a success factor for traditional companies. For example, because of its tense financial situation, AMD changed from IDM to fabless and sold its factories, which were then reconstituted as a new foundry company (Robertson, 2008). Mixed models also exist, where IDMs outsource only parts of the production line or dedicated products. Foundry businesses focus on the frontend parts of the SI value chain, which includes chip technology. Another business model is called OSAT and is concentrated on the backend parts of the SI value chain (Naeher et al., 2011). A further type of business model is IP licensing. For an annual fee, this model allows companies to use the design of other companies that own the IP of this semiconductor design. A well-known licensor in SI is ARM, which owns IP for smartphone and tablet processors (McGregor, 2016). Another segment in SI is the manufacturing of capital equipment that is required for fabrication of semiconductor devices.

The value-creation in SI can be divided by business model to reveal further insights about profitability. Figure 2-2 shows the results from 2013 to 2017 based on the data from a McKinsey study (Jong and Srivastava, 2019). It clearly shows that IDM companies (including microprocessors and memory) dominate the industry by earning 50% of total economic profit. The fabless companies followed at the second position with almost half of the profit of IDMs. Foundries and capital equipment manufacturers had nearly the same profit each as a third of the fabless companies. At a significant distance, IP companies reached a profit of $1.8 Billion. OSAT companies had a negative result of $-0.6 Billion.

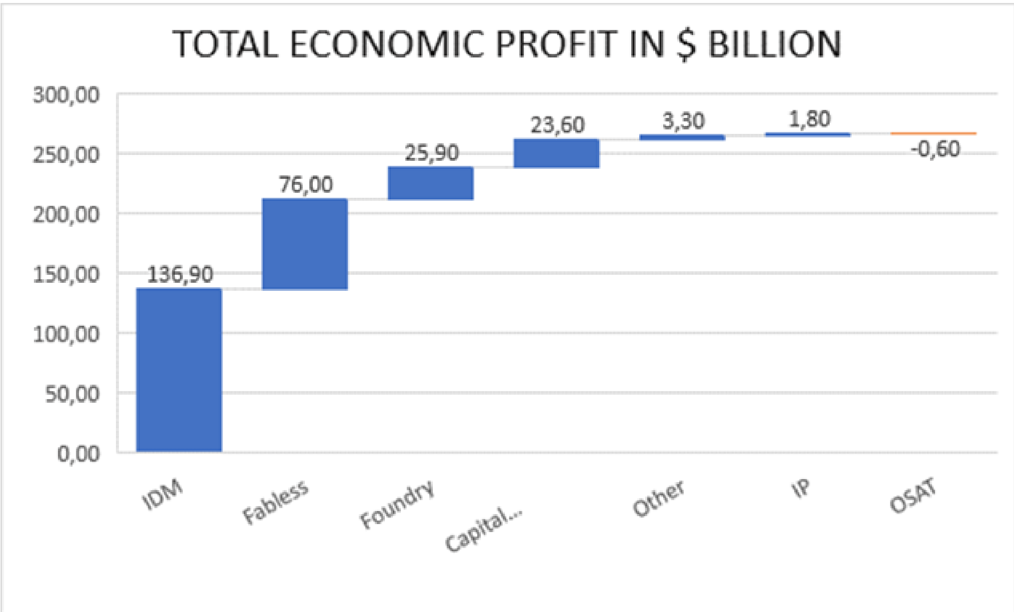


Figure 2-2: Total Economic Profit in SI from 2010 to 2017 by Business Model based on data taken from Jong and Srivastava (2019, p. 6)

SI companies operate from all over the world, however, the global sales share differ significantly between the regions. In 2017, China owned the largest sales share (32%) followed by Asia Pacific (28%) and the Americas (22%). Europe and Japan were on a par with 9% sales share each. Overall, the global total revenue in 2017 was $ 412.2 Billion (McGrath, 2018). Though the sales increased during 2018, there was a significant sales loss of 12% in 2019. Factors such as Brexit and American trade wars influenced the global economics in a negative way, including the SI. In particular, for the SI, the Americas lost the most sales by far (-23.8%). Other regions lost as well, but not as much as the Americas: Japan (-10%), Asia Pacific (-9%), China (-8.7%) and Europe (-7.3%) (Semiconductor Industry Association, 2020). Though previous forecasts for 2020 were positive (Gartner as cited in Singer, 2020; PricewaterhouseCoopers, 2019), Gartner (2020) updated its prognosis and expected a revenue decline of 0.9% due to the Covid-19 pandemic. This modification indicates the significant economic impact of the pandemic on SI.

SI provides various products for different customers and applications. According to PricewaterhouseCoopers (2019), the products can be categorized by:

- **Memory**: Semiconductor components such as dynamic random access memory, flash memory and solid-state drives.
- **Micro-component**: Semiconductor components such as microcontrollers, real-time sensors and microprocessors.
- **Logic**: Semiconductor components such as application-specific integrated circuits and application-specific signal processors.
- **Analog**: Semiconductor components such as power supply chips or wideband signal devices.
- **Optoelectronic, sensor and discrete components (OSD)**: Semiconductor components such as light-emitting diodes, lasers and image sensors.

Despite the tense economic situation in 2020, it can be expected that SI will still gain the sales increase that was predicted earlier for those applications once the Covid-19 crisis is over. Some of the main drivers for this prospective positive trend are the ongoing technological advancements in cloud computing, consumer electronics, car safety systems, smart-grid energy or internet-of-things, for example. Since it was forecasted that these applications would also increase their demands and sales volumes over the following years (PricewaterhouseCoopers, 2019), SI as a technology supplier is likely to benefit from these trends. It is not evident from recent articles that these mid-term trends caused by the Covid-19 pandemic would flatten or even decline. On the contrary, the lockdown situations in multiple countries have reinforced the importance of digital services such as collaboration and conference tools, by which companies such as Microsoft and Zoom could gain long-term benefits (Vontobel, 2020). The infrastructure behind these services also requires semiconductor devices. In addition, it is believed that virtual classrooms, digitalization in public sectors and healthcare and similar trends will gain increased attention. This is because neither companies nor governments can afford to experience the negative impacts from these lockdowns again in future. They have to foster the transfer of traditional processes towards time- and location-independent processes that are supported by digital services. Overall, SI could take advantage of the current economic crisis with a long-term view due to the changing digital requirements and opportunities in multiple national societies.

2.2.2 Optoelectronic Industry

In this thesis, the method for primary data collection is the case study. The selected company for the case study is in the optoelectronic segment of SI. Therefore, the background and market for optoelectronic devices is discussed in more detail within this sub-section. Optoelectronic devices can be light-emitting or light-absorbing. As well as being products that produce visible light, optoelectronic devices can also generate infrared or ultraviolet light that is not visible to the human eye. Table 2-1 lists the types of optoelectronic products and their present applications based on Fox (2019).

The global long-term sales forecasts for optoelectronic components are generally optimistic. However, not all product types show the same positive trend. A particular forecast compares data from 2018 with predicted values for 2024 (Fox, 2019, p. 17). It suggests that the market will only grow considerably for LEDs (+2.4%) and isolation products (+3.4%). Based on the detailed data, the market development for optical switches is expected to decrease by 0.3% whereas the revenue for LED displays will stagnate. Infrared components will increase their revenue by at least 0.8% according to the prediction. IC Insights (2020) pointed out that the sales of optoelectronics in 2020 are expected to decrease by 6% compared to 2019 due to the Covid-19 pandemic. However, they predict a sales increase of 10% for 2021 and a further growth over the next 5 years. This trend is driven by applications such as CMOS image sensors for embedded cameras, automotive safety and 3D imaging.

Table 2-1: Optoelectronic Product Types and Economic Trends based on Fox (2019, pp. 21–119).

Product Type	Present Applications
Visible Light-Emitting Diodes (LED)	• General lightning and signage • Automotive exterior and interior • Consumer electrics, e.g., mobile handsets • Horticulture
Isolation	• Automotive, e.g., optocouplers for vehicles • Telecommunications, e.g., smartphone chargers • Computer and office equipment, e.g., power supplies • Special products for military and aerospace • Industrial, medical and security, e.g., motor drives
Infrared	• Biometrics, e.g., 3D face recognition and iris scan
Optical Switches	• Automotive, e.g., rain sensors • Computer and office equipment, e.g., detection of paper presence in printers • Industrial, e.g., automatic assembly
LED displays	• Application in several sectors such as industrial, medicine, military and aerospace
Ultraviolet LEDs	• Nail polish curing • Banknote counterfeit • Horticulture lighting • Tanning • Health care equipment • Disinfection for water, air, food, textile • Surface sterilization • Water and air purification

Figure 2-3 illustrates the companies that fabricate optoelectronic devices and their global market share based on data from Fox (2019). The market leaders are Nichia and OSRAM Opto Semiconductors followed by Lumileds, Seoul Semiconductor and MLS.

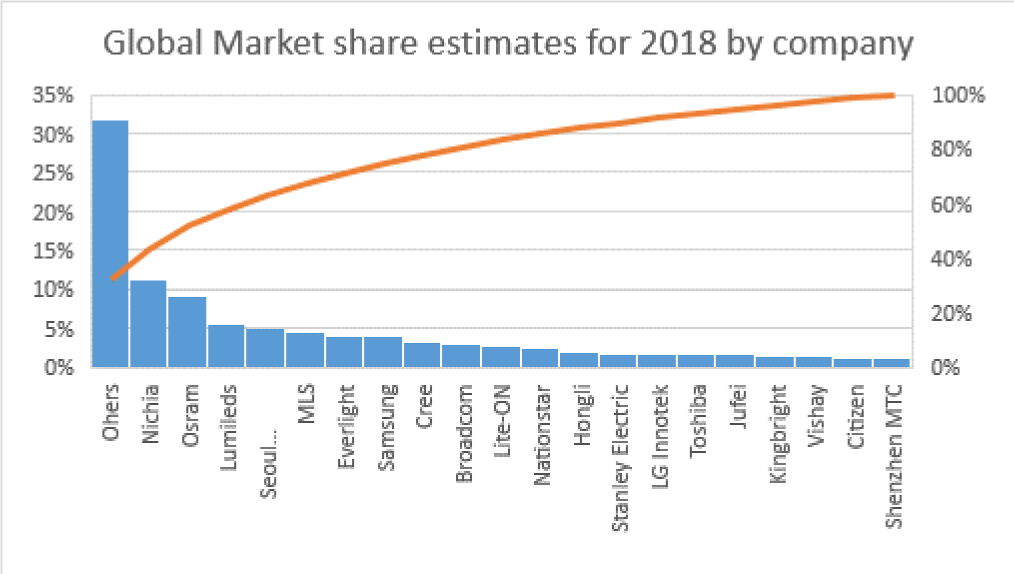


Figure 2-3: Global Market Share Estimates for 2018 by Company based on Data taken from Fox (2019 p. 20)

The global market can be divided by the most important customer regions for optoelectronic components. Greater China owns 50% of the market share, followed by the rest of Asia Pacific (15%), Western Europe and Japan (both 11%) and North America (9%). The remaining portion is shared by Eastern Europe, South America, Middle East and Africa (Fox, 2019, p. 19). The comparison shows that China and Asia Pacific lead the optoelectronic market even more than the rest of SI. From recent articles, it is not evident that the Covid-19 pandemic would have any perceptible impact on this distribution.

2.2.3 Semiconductor Value Chain

The design and fabrication of semiconductor components is a high-technology process. The components fulfil critical functions within their target applications and the customer businesses are very diverse as discussed earlier in this section. Even IDMs operate factories in different global regions depending on the process requirements that a factory must fulfil. Global SI leader, Intel (2011), separated its facilities by ‘wafer fabs’ and ‘assembly and test’. Wafer fabs are responsible for the chip fabrication and testing on wafer level. This stage in the manufacturing process is also called ‘frontend’. Once the chip circuits meet the specifications as designed, the finished wafers are sent to an assembly facility. At this stage, wafers are cut and separated into microprocessors. Each single chip – also called 'die' – is assembled into a package for protection, critical power and electrical connection. After a final test of each package, the finished devices are distributed to customers. All process steps between frontend and distribution are also known as 'backend'. The report indicates that the majority of Intel's wafer fabrication facilities are based in the USA, whereas most of the assembly and test facilities are located in Asia, and none of them is located in the USA. This constellation leads to a globally distributed but geographically concentrated value chain. A report from Alam et al. (2020) pointed out that this type of global value chain is typical in SI. The report puts the number of countries that are participating per stage in the industry-wide value chain as: chip design (12 countries), wafer fabrication (39 countries), assembly and test (25 countries). In addition, the semiconductor device manufacturing process requires a variety of raw materials. A selected but unnamed US-based SI company has over 16,000 suppliers worldwide (Nathan Associates Inc., 2016). All of these characteristics lead to a complex supply and production network in SI.

A report from Deloitte (2020) discussed the long-term implications of Covid-19 on SI value chains. It highlighted the risks of cost-driven geographical concentration, which led to single points of failures within the global value chain during the pandemic. To overcome this risk, the authors suggested going away from this type of model towards a more agile supply network. However, the article did not explain fully how a SI company should manage such a challenging change. For instance, it is not believed that established manufacturing processes can be moved to countries where SI is not present so far without losing process efficiency and product quality. The detailed configuration of machines and recipes is an iterative, time-consuming and cost-intensive process that is required to achieve a sufficient level of maturity. In addition, the geographic concentration has produced important labour markets from experienced operators to highly skilled engineers. SI companies benefit from engineers and managers who change employers and contribute with their expertise. It would take several years or even decades before a similar labour market could be established in countries that are new to SI (Scott, 1987). Without such a regional labour market, the sourcing of necessary experts would become complicated. Further efforts must be considered that are required for coordinating an even more complex supply network. Therefore, the proposal of Deloitte cannot be agreed as it would lead to significant disadvantages to the value chain.

An established model to visualize and analyse value chains especially for manufacturing businesses was proposed by Michael Porter in 1985 (Mozota, 1998). This model divides company activities into primary and support. However, this model shows a number of limitations when applying it to SI:

1. The primary activities are organised as a linear sequence. Because products can be manufactured internally as well as externally (at foundries and OSATs), inbound and outbound logistics must be triggered multiple times in different orders for various products. Porter's model does not consider this type of flexibility in logistics.
2. Products that are more complex do not have one particular origin of manufacturing, but can root in multiple independent value chains. For instance, there are products that have already passed the backend stage only to be sent again to the frontend for advanced processing (e.g. LED panels). Porter's value chain model is not able to address such a constellation.
3. SI is highly dependent on RnD of products and processes. Observations in real SI companies show that RnD activities are strongly integrated with manufacturing activities. This integration is necessary in order to be responsive in the case of process deviations or to decrease the time to market for new products, which is a crucial success factor due to short product lifecycles (see 2.2.4). According to Porter's model, RnD activities would be classified as 'support', whereas in reality RnD is part of the primary SI value chain. This objection is also reflected by SI value chain models from PricewaterhouseCoopers (2019), Alam et al. (2020) and Nathan Associates Inc. (2016).

Since Porter's model does not fit SI, a different model is proposed for this thesis to visualize the SI value chain. Figure 2-4 is inspired by Nathan Associates Inc. (2016, p. 4) and puts the key characteristics together into a value-chain-directed SI ecosystem. Support activities such as infrastructure and human resource management are excluded because they are not relevant to this thesis.

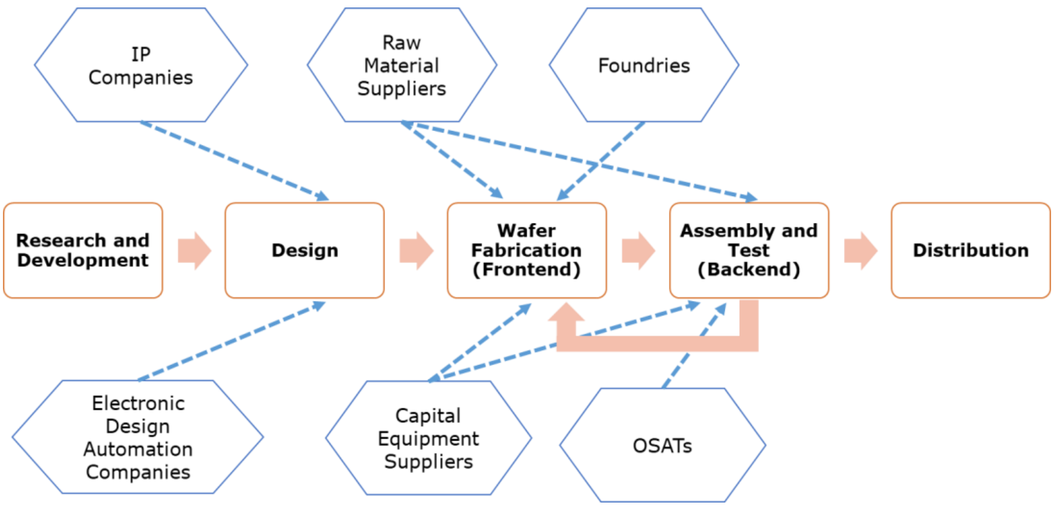


Figure 2-4: Value-chain directed SI Ecosystem inspired by Nathan Associates Inc. (2016, p. 4)

Prior to the manufacturing of semiconductor devices, semiconductor companies conduct RnD to drive process innovations. Nathan Associates Inc. (2016) pointed out that SI belongs to the most research- and development-intensive industries in the world with industry-wide investment rates ranging between 15 and 20 % of sales. At the design stage, new products and specifications to meet customer needs are developed. The outcomes of the research and development stage are the key input to the design stage. Moreover, the design stage can be supported by, or even depend on, IP companies for design licensing or electronic design automation companies that provide specific design services. The designed chips are handed over to the wafer fabrication stage followed by the assembly and test stage. Both stages interact with external partners to obtain raw materials and capital equipment that provide specialised tools for the manufacturing requirements. As discussed in 2.2.1, the wafer fabrication can be outsourced to foundries and the assembly and test can be outsourced to OSATs. For special products, it may be necessary to send chips that have passed the assembly and test stage back to the wafer fabrication. Finally, the finished goods are distributed to the customers.

2.2.4 Challenges in SI Value Chains

As presented in 2.2.3, the constitution of SI value chains produces considerable complexity even on a high level. Looking into the manufacturing and supply chain processes, further complexity drivers and challenges can be identified. These challenges are especially valid for SI and can be grouped by areas to understand the most influencing ones. Figure 2-5 presents the areas and numbers of associated challenges. Overall, 29 challenges could be identified in the literature.

The figure shows that most of the challenges are related to ‘logistics’ (10), followed by ‘product management’ (6), ‘data and IT’ (4), and ‘engineering’ (3). Less challenging areas in the context of manufacturing are ‘quality’ and ‘organization’ (2 each) as well as RnD and ‘costs’ (1 each). Several challenges can be logically connected even across these areas. For instance, Fordyce (2012) emphasized that high capacity utilization is an important challenge. It can be associated with the area of ‘logistics’. Its importance is driven by the expense of capital equipment especially at the wafer fabrication stage. Managing these expenses appropriately is another challenge, which is related to ‘costs’. In the end, poor utilization affects the finished good costs in a negative way.

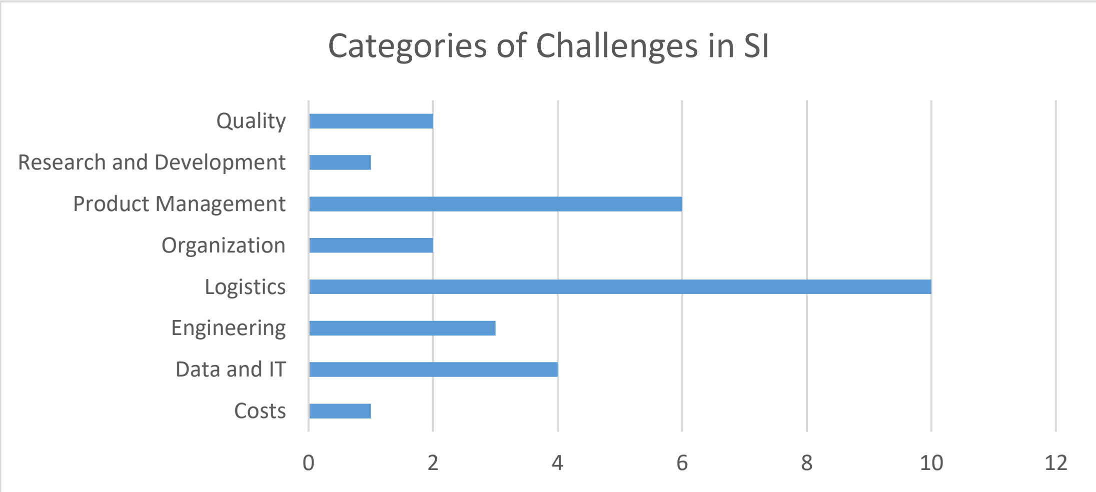


Figure 2-5: Areas of Manufacturing-related Challenges in SI based on the Literature

Hence, the importance of these challenges can be agreed as they directly affect the economic results of a company. In the area of ‘product management’, a number of challenges is concerned with product lifecycles. Forster et al. (2013) pointed out that SI deals with rather short product lifecycles compared to other businesses such as the automotive industry. This leads to the challenge of constantly introducing new products efficiently. Another issue that is addressed to ‘product management’ is the diversity of the customer businesses. It can be implied that this diversity leads to very different product life cycles. For instance, components for smartphones are dependent on the rather short product lifecycles of smartphones. Though the selling trend from 2013 to 2016 indicates that customers keep their smartphones longer before upgrading to a new one (Armstrong, 2017), an average product lifecycle of 21.5 months can be seen as ‘short’ if a product costs between $ 200 and $ 700 on average (Statista, 2016). In contrast, the product age of cars in Germany in 2015 was nine years on average (ACE, 2015). Therefore, an optoelectronic company that supplies both customer industries must manage various product life cycles that partially affect the same goods.

In the area of ‘Data and IT’, Sun et al. (2016) pointed out that observations show that SI managers and engineers tend to prioritize urgent operational needs rather than standardization. This type of prioritization leads to a growing number of so-called ‘quick fixes’ that solve a particular problem fast, but leads to high risk and uncertainties for the whole value chain. It is believed that this type of prioritization will have a long-term negative influence on the operational efficiency:

- The creation of isolated solutions for single departments will be fostered, by which central services and data harmonisations are hindered.
- Thereby, significant efforts for data discovery and cleansing must be spent to use important data from these isolated systems in central solutions or reports.
- Hence, managers work with uncertain reporting results, which may lead either to poor decisions or to additional efforts to clarify the correctness.

Villareal et al. (2018) discussed the strengths of big data applications to overcome IT-related challenges in SI. They claimed that SI companies fail to make use of the information that is generated during the manufacturing process especially at the wafer fabrication stage. Generated data is either stored and not used or even not stored at all. The authors justified this by citing mainly technological issues, e.g. missing database scalability and poor performance of data analysis hinder companies to make use of this data. However, it is not believed that data would be used more effectively only by upgrading the IT infrastructure. As discussed in the previous paragraph, SI value chains suffer from non-standardized and isolated IT solutions. Without harmonizing and sustainably managing the enterprise data architecture, big data applications are not able to gain value from the heterogenic and partially inconsistent data.

Fielden (2018) pointed out that the continuous scaling of circuit density, computational power and energy efficiency becomes challenging without effective technologies for inspection and metrology. In fact, the testing capabilities of an SI company and the spent efforts for testing may have an impact on both product quality and cycle time. This challenge of keeping the testing efforts low is associated with the area of ‘engineering’.

Further challenges are summarized in the conceptual framework in 2.6. Some of the challenges are expected to be mastered by PA that is discussed in the following section, 2.3.

2.3 Definition and Overview of Predictive Analytics

In this thesis, a literature research has been carried out in order to assess the historical trends in PA and to contextualize them with trends in the related areas Machine Learning (ML) and Data Science (DS). Figure 2-6 visualizes the development of publications that are associated to each area from 1990 to 2020. Since the actual numbers differ significantly, the bars present the percentage of publications per area and time period in relation to the sum of publications over the past 30 years. In addition, the lines highlight the percentage differences between the periods and indicate the trend directions.

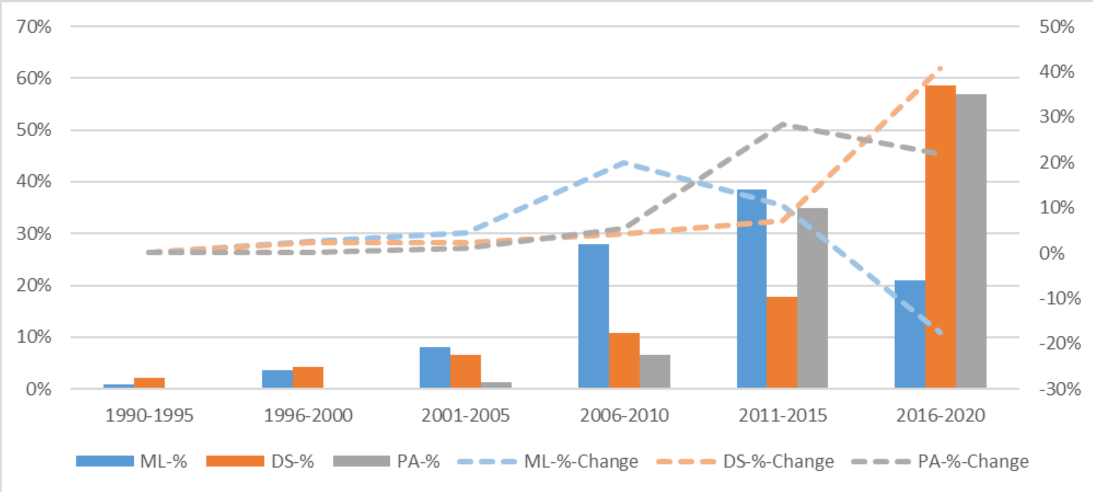


Figure 2-6: Trend Comparison of Publications in the Areas of Data Science, Machine Learning and Predictive Analytics

The analysis and evaluation of the research results led to following findings:

- There was a general increase in all areas from the early 2000s onwards, however, different trends can be stated. ML was the first area that received noteworthy attention and showed the biggest increase of publications between 2006 and 2010 (+20%). Though the number of publications increased further and peaked between 2011 and 2015, the slope decreased and turned even into a negative trend between 2016 and 2020. In contrast, PA started to gain attention in the upcoming period from 2011 to 2015. Though the majority of articles were published during the past four years, the trend indicates a slightly decreased slope (from +28% to +22%). The third area, DS, shows another different trend with a significant increase of publications from 2016 to 2020 (+41%) after an average slope of +4% during the upstream periods.
- In spite of the negative trend are the actual numbers of publications in ML still significantly higher than in the other areas. Considering the total number of related publications from 1990 to 2020, the areas of DS (129.410 publications) and PA (46.111 publications) are far behind ML (3.610.600 publications). These differences indicate that the research in this area is much more established.

To understand the different trends despite the strong associations between these areas, clearer definitions and demarcations are required. Many researchers treat ML as a sub-discipline of ‘Artificial Intelligence’, e.g. Chris Huntingford et al. (2019), Alimadadi et al. (2020) and Rauschert et al. (2020). Alpaydin (2020) highlighted that ML aims to solve a given problem by programming computers to use example data or past experiences. The area of ML is often divided by learning type, which means that associated ML techniques can be classified as either ‘supervised’ or ‘unsupervised’. Supervised learning uses labelled data to identify relations between input and target variables, where a label represents a desired output. These relations are used to gain predictions in new data sets. Unsupervised learning makes only use of input data points in order to identify the organizing principles within the data set, whereas the desired output is not known (Ceriotti, 2019; L'Heureux et al., 2017). Some established ML techniques are support vector machines, artificial neural networks and clustering (Hesami et al., 2020; Hong et al., 2020; Mirmozaffari et al., 2020; Zhang et al., 2020). From the literature review it can be implied that the term ML is strongly related to the mathematical core techniques rather than to engineering topics such as improving database performances or implementation of IT tools that apply ML. For instance, Vo et al. (2019) discovered the capabilities of unsupervised learning for image matching based on mathematical optimization, which is able to limit human labelling efforts. In addition, the problem statements in ML are beyond economic applications such as in manufacturing or e-commerce: Lillicrap et al. (2020) assessed the impacts of backpropagation on the learning mechanisms of the brain, Soltis et al. (2020) discovered the applicability of ML for plant biology and Tate et al. (2020) proposed a ML-based model to predict mental health issues to name just a few.

Based on the reviewed literatures, a clear and widely established definition of DS does not exist. Some authors like Nosratabadi et al. (2020) see DS as application of ML and deep learning. Steinwandter et al. (2019) considered several techniques to implement a DS project such as multivariate equivalence testing, principal component analysis, artificial neural networks and knowledge management. Boehmke et al. (2020) defined DS as combination of important skills, which are programming skills, analytics skills and domain expertise. A similar but more advanced definition was proposed by Aunkofer (2020), who considered following skills in order to apply DS: (1) Expertise, e.g. finance and supply chain, (2) DS methods, e.g. ML and statistics, (3) DS tools and libraries, e.g. TensorFlow and Scikit-Learn, (4) programming language, e.g. Python and R, (5) data access and transformation, e.g. data streaming and data security, (6) database technology, e.g. SQL and InMemory. However, Singleton and Arribas-Bel (2019) demarcate DS particularly from the term ‘Big Data’ and summarize it as ‘processes and techniques involved in turning (…) resources into insight and understanding’ (p. 2). Hence, they did not see the technical levels of data processing as part of DS. This view was shared by Bolard (2018) who proposed that DS consists of (1) data exploration and transformation, (2) aggregation and labelling and (3) learning and optimization, whereas the technical parts are related to ‘data engineering’. In addition, AI and especially deep learning were demarcated from DS, which is contradictory to Nosratabadi et al. (2020). Though the literatures did not provide a clear definition of DS, the importance of the term in academic research increases significantly as visualized in Figure 2-6. Such a development indicates that DS is rather a buzzword than a particular discipline. This view is also shared by many authors such as Golombek (2020), Mishra et al. (2020) and Nield (2019).

From a methodical perspective, PA uses a similar set of statistical and analytics techniques as the related and previously established discipline data mining (DM). These techniques allow the extraction of new information from data and the prediction of trends and effects (Finlay, 2014). The methodical overlaps of DM and PA partially lead to the assumption that both terms refer to the same approach. On the one hand, some authors argue that the targets of the two disciplines are not identical. For example, whereas DM is mainly concerned with finding new relationships in large amounts of data, PA is focused on the prediction of future trends, events and behaviour patterns (Hair, 2007). On the other hand, Abbott (2014) admitted that he uses DM and PA synonymously and Gulati (2015) literally proposed DM techniques to apply PA. At least it can be implied that one could separate PA from DM by defining areas of application. However, due to the methodical overlaps, a separation is not necessary.

The statistical techniques behind PA and DM were developed between the end of the 19th century and the 1920s. The exploratory data analysis, based thereon, was proposed in the 1970s (Hair, 2007). Therefore, it can be criticized that both terms only consolidate and reuse selected techniques that already existed. It is not evident from the literature that the actual foundation of DM and PA as separate disciplines contributed anything fundamental to science or economics. Therefore, both terms have the character of a buzzword. This assessment is also supported by Chahal et al. (2019) and Ripley and Chen (2003). The latter claimed that DM is mainly used for the re-marketing of previous ideas from statistics and machine learning (ML) and to commercialize associated solutions. Indeed, the global big data market size, which is related to PA as mentioned by Siegel (2013), quintupled between 2011 and 2017 from $ 7.6 billion to $ 35 billion (Holst, 2020). Nevertheless, and despite the mentioned explanations from Siegel, the question is not clearly answered by the literature: is this success influenced by the importance of PA – or is the importance of PA caused by the success of big data? At least Sathishkumar et al. (2020) stated that ‘as data availability increases, the accuracy of the algorithm also improved’ (p. 971). Thus, as Holst (2020) forecasted that the big data revenues continue to increase over the following years, it can be expected that the importance of PA will correlate to this trend.

Since the point of interest is located in the future, an exact prediction is usually not possible. Therefore, to deal with this kind of uncertainty, PA works with scores and probabilities. The following example illustrates this approach:

> A trading company wants to calculate the product demand d_{t+1} for the next order period to adequately restore their stocks. Primarily, they will put the historical sales data and apply predictive algorithms, e.g., exponential smoothing. They will also add seasonal or regional factors and include information from market development studies to improve the predictive result. Thus, the result d_{t+1} can reach a reliable level. Nevertheless, it remains only a probable result. The company needs to add further statistical calculations to set a reliability interval from x to y

around d_{t+1}. In the end, they can state: with a probability of 95%, the demand for period $t+1$ will vary between x and y (Herrmann, 2009).

Gronwald (2015) classified the approaches in analytics into five categories: (1) descriptive analytics, (2) predictive analytics, (3) prescriptive analytics, (4) sentiment analysis (SA) and (5) text mining. He defined each category with the orientations, techniques and goals. This classification shows that it is necessary to define the goal before selecting an appropriate approach. For instance, prescriptive analytics focuses on the underlying causes as well as the predicted result while PA only focuses on the predicted result without asking 'why' an analysed entity will develop as calculated. In addition, this classification provides a clear overview of the various capabilities of data analytics. However, the classification does not make clear that there is a difference between the maturities of the approaches. Lepenioti et al. (2020) pointed out that prescriptive analytics is still less mature than descriptive and predictive analytics. Furthermore, it is doubtful that SA fits into this classification. All other approaches use raw data that is typically system-generated (e.g. MES timestamps, product measurement, telemetric data of equipment), whereas SA uses subjective data gathered directly from humans. López and Cuadrado-Gallego (2008) stated that SA is an application of natural language processing that belongs to the area of artificial intelligence. This type of classification is reasonable and supports the idea of separating the raw-data-based approaches in data analytics from SA and text mining due to substantial differences of methods, input data and areas of application.

A notable finding from the literature review is that the number of articles increased disproportionately that focus on PA in the context of manufacturing. The trend shows that the percentage of manufacturing-related articles was at 34% in the early 1990s. However, it seems that PA researchers changed their focus during the following years, because they discussed applications in manufacturing in less than 10% of all articles until 2005. From this time forward, the attention on manufacturing aspects increased significantly. Between 2011 and 2015, 27% of all articles are related to manufacturing, and between 2016 and 2020 the percentage reached 54%. It can be assumed that this high increase is related to other technological trends in the area of manufacturing. To prove this hypothesis, further research was performed to extract the number of articles that are employed with data-related trends in the area of manufacturing. Figure 2-7 presents the search results in relation to the percentage of manufacturing-related PA articles.

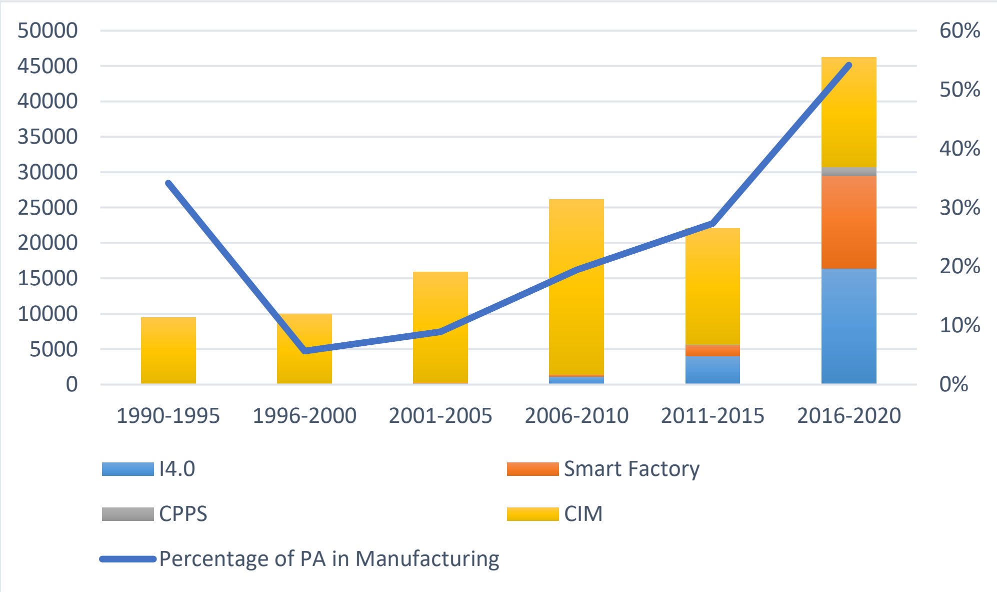


Figure 2-7: Number of Articles concerned with Data-related Trends in Manufacturing

The results indicate that there is a general relationship between the importance of PA in manufacturing and other trends such as ‘smart factory’, the German ‘Industry 4.0’ (I4.0) and ‘cyber physical production system’ (CPPS). The longer-existing trend ‘computer-integrated manufacturing’ (CIM) correlates to the importance of PA in the period from 2001 until 2010. Between 2011 and 2015, the overall number of articles decreased, which is mainly a result of reduced attention to CIM. Nevertheless, new trends such as CPPS and I4.0 disproportionately gained attention compared to the previous period. This particular increase correlates to the growing percentage of manufacturing-related articles in the area of PA. Furthermore, there was a rapid rise of articles for both data-related trends in manufacturing and manufacturing-related articles in the area of PA from 2016 to 2020. Therefore, it can be concluded that both courses are related and there is an increased importance of digitalization, especially of data-based automation and decision-making in manufacturing business.

In order to narrow down the key intentions of the core terms associated to this research and how they are logically related, Figure 2-8 presents a contextualization that is based on the review of definitions and associated research projects.

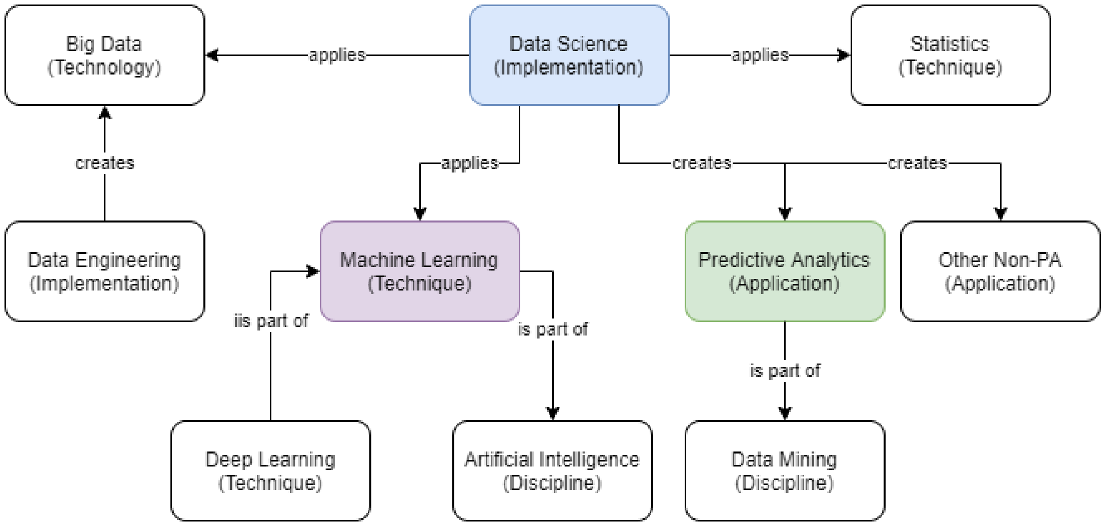


Figure 2-8: Contextualization of Major Terms related to PA

The figure suggests to treat DS as an implementation approach that combines and applies Big Data, Statistics and ML in order to create a PA application. PA itself is seen as part of the discipline DM, whereas ML is seen as part of the discipline AI. In addition, it must be emphasized that DS does not only create PA applications but other types of applications with different goals. Based on these relations and previous discussions, the different research trends visualized in Figure 2-6 could be explained as follows:

- ML provides the fundamental techniques that are required to build PA solutions, hence, the attention on methodical issues increased chronologically earlier than on applications. Many publications present basic research in ML, which could be a driver for the much higher number of articles in this area compared to applied research in DS and PA.
- The growing importance of PA was driven by digitalization initiatives in the manufacturing area and can also be stated for other technological

trends. In order to accomplish the goals of Industry 4.0 and similar concepts, ML was applied to generate new insights from data, where predictive capabilities are crucial to minimize failures, material waste and other types of production costs.

- DS has been found as an implementation approach that applies several techniques such as ML and Statistics in combination with Big Data technology. PA applications may be one type of output from DS initiatives, however, the literature review shows a broader spectrum of applications. Due to this relation, the total number of articles in the area of DS surpasses PA. The broader applicability of DS could also explain the significantly increased importance of DS during the past four years, where more and more disciplines (e.g. medicine, biology and geography) assessed potential fields of use for DS.

2.4 Methods of Predictive Analytics

Based on the findings from the current literature review, PA is not defined by a fixed set of methods. It is assumed that a major problem in identifying commonly accepted methods lies in the fact that PA itself is not consistently defined. The following list shows different scopes and thematic separations for PA:

- Larose and Larose (2015) divided PA and DM into exploratory data analysis, statistical analysis, classification, clustering and association rules.
- Kotu (2015) divided PA and DM into data exploration, classification, regression, association, text mining, time series forecasting, anomaly detection and features selection.
- Abbott (2014) divided PA into data understanding, data preparation, item sets and association rules, descriptive modelling, predictive modelling and text mining.
- Barga et al. (2015) referred to applied PA with Microsoft Azure and divided PA only by statistical and ML algorithms.
- Finlay (2014) referred to both particular methods (e.g., support vector machines (SVM), expert systems) and groups of techniques (e.g.,

linear models, clustering) to separate the types of PA models. Other activities such as data exploration and preparation were treated as part of the PA development process.

- Mauerer (2020) highlights the overlaps between PA and DM, where PA exceeds the scope of DM by application of advanced techniques such as Simulation and Text Mining.
- Adobe (2020) considers ML, statistics and DM in order to apply PA and emphasizes regression, decision trees and neural networks.

The comparison of the literature leads to several findings. As already discussed in 2.3, PA cannot be fully delimitated from DM due to the significant overlap in methods and aims. In addition, text mining and descriptive analytics are seen as part of PA (e.g., by Kotu (2015)), which was clearly disagreed by Gronwald (2015). Furthermore, the activities in the area of PA are not clearly specified. Some authors refer to PA as the entire process to implement a predictive solution (e.g., Abbott (2014)), whereas others separate the actual prediction models from upstream or downstream tasks (e.g., Finlay (2014)). Beyond the inconsistent use of terms, the authors do not match with the selected prediction techniques, for instance:

- Finlay (2014) proposed expert systems as one type of predictive model, which is not considered by any other author.
- Kotu (2015) and Finlay (2014) proposed support vector machines for classification, which is not considered at all by Abbott (2014) or by Larose and Larose (2015).
- Larose and Larose (2015) defined clustering as a type of descriptive modelling, which they separated from predictive modelling, whereas Finlay (2014) proposes clustering as a predictive model.

To gain a clearer understanding, it is suggested that PA methods should be classified as either supportive (e.g., data preparation) or core (e.g., regression). A full PA application requires both types of methods to be applied during the development process. If a supportive task such as data preparation becomes a regular task for the PA application, it might also be an integral part of the solution. Though only the core methods are capable of prediction, it is believed that only a PA application as a whole is able to generate benefits for a company. In particular, the maturity of data preparation can be seen as a success factor for reliable predictions. Techniques such as correlation analysis and principal component analysis can be applied to PA projects for this purpose. For instance, Budgaga et al. (2016) discussed them in terms of dimensionality reduction, which is an upstream step to limit the input variables for the actual prediction model. Gogtay and Thatte (2017) pointed out that 'correlation analysis stops with the calculation of the correlation coefficient and perhaps a test of significance' (p. 81) and that usually regression analysis is also applied in order to achieve predictions. This statement supports the idea of dividing PA methods into supportive and core.

Since PA as a term, as well as the underlying methods, are not clearly defined by literature, it is not believed that any benefit could be calculated on this broad level. In addition, it can be implied from the previous findings that PA does not only mean a particular prediction technique, but includes upstream activities such as data discovery and preparation. Therefore, it is not believed that any benefit could be determined for single PA methods such as artificial neural networks or naïve Bayes classifiers. Instead, it is proposed to discover how PA can be applied to SI manufacturing in oder to overcome the identified challenges. According to Finlay (2014), PA can be applied to improve the efficiency of a process, to enable better decision-making or to enable a new activity that was not possible before. For instance, Rauniaho-Mitchell (2020) proposed applying PA in order to optimize the material flow within a factory. Since PA is capable of detecting anomalies in historical data, it could identify those anomalies that have generated bottleneck situations in the past. By applying this knowledge to real-time data, bottlenecks could be predicted based on topical anomalies, and production managers are able to act before the issue occurs. It was noted that Rauniaho-Mitchell (2020) did not refer to any particular PA method that is used for this scenario without giving reasons. The implicit reason could be that the method itself does not matter as long as the results of the whole PA application meet the expectations. In fact, Mishra and Silakari (2012) pointed out that the development of a DM solution requires testing multiple predictive techniques against a set of case-specific validation data. They explained that the validity of the tested techniques could be expressed by the prediction error that is measured, for instance, by average error, total sum of squared errors, or root mean squared error. Professional software for developing PA applications such as IBM SPSS provides features to compare the validity of various predictive models (El-Shimy, 2018). In addition, D'Haen et al. (2013) demonstrated that the type of data preparation, such as combining different data sources instead of using them independently, could influence the performance of a predictive technique. The fact that validity and performance of a core PA method highly depend on the specific case data underpins that a general benefit of single methods for SI PS cannot be calculated. Instead, it is believed that the benefit of PA results from the improvements that are gained by applying a PA solution to a particular business process. Hence, it is proposed to focus on PA applications that are crucial for semiconductor manufacturing in order to discover which process improvements they would generate, which specific challenges they would master, and which types of benefits to PS performance would arise.

2.5 Predictive Analytics Applications in Semiconductor Manufacturing

2.5.1 Overview

A literature research has been carried out in this thesis to discover the importance of PA in SI and in which way it has developed over the past 15 years. Figure 2-9 shows the yearly development of publications that are concerned with PA in semiconductor manufacturing from 2005 to 2020. Based on these numbers, it appears that PA was less important to SI before 2010. Only a small number of articles and theses were detected that were employed on this topic at that time (e.g. Barbee (2007)). Since 2010, there has been a positive trend in general, such as with studies from Meidan et al. (2011) and Moyne et al. (2014)) that turned into a significant increase from 2017 to 2018 (e.g., with studies from Chiu et al. (2017) and Liao et al. (2018)). This increase correlates with the data-driven trends in manufacturing that have been identified and discussed in 2.3. From 2018 to 2019, the number of articles stagnated. The value for 2020 is forecasted based on the previous number at the time of the review. This forecast suggests that in 2020 at least a similar number of articles will be published as that in 2019.

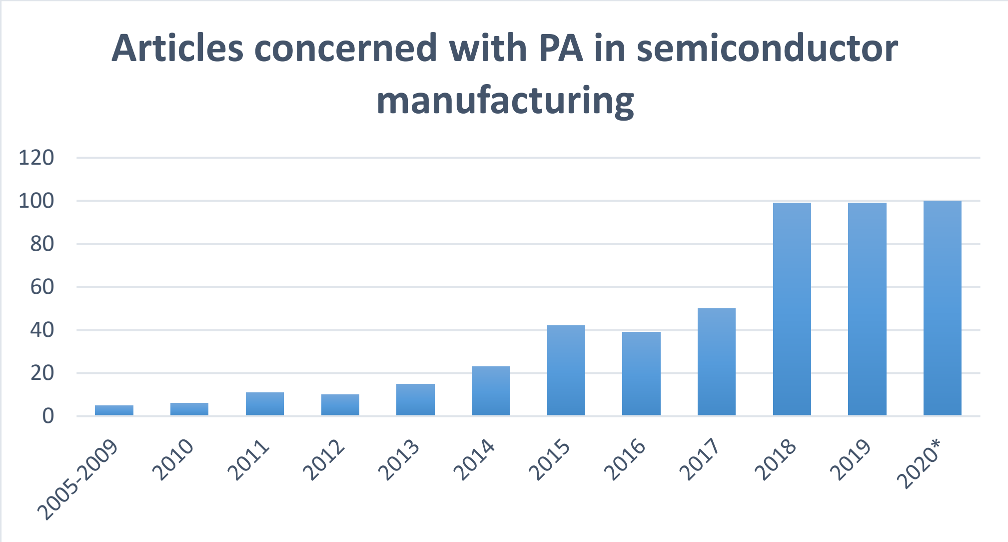


Figure 2-9: Number of Articles concerned with PA in Semiconductor Manufacturing

The titles of the overall 443 articles can be divided into single words to analyse the occurrence of each term in this research context. Figure 2-10 visualises the number of occurrences as a word cloud. It indicates, for instance, that there is a significant relationship with activities in ‘Big Data’ and ‘Machine Learning’. The numbers of occurrences are only raw data that do not recognize compound terms (e.g., ‘Big Data’ or ‘Data Mining’) and does not exclude auxiliary words (e.g., ‘using’ or ‘based’). To gain insights into which majors and conceptual relationships exist, a more specific analysis is required. The weighted data behind the word cloud acts as the basis to search for relevant (compound) terms within the titles of the articles. The coding technique is applied to group different but related terms, and the articles are classified by codes. The codes are then classified as either application of, or technology for PA.

Figure 2-10: Word Cloud for Terms that are concerned with PA in Semiconductor Manufacturing (own visualization)

Figure 2-11 shows the results of this analysis. Overall, 208 articles can be classified by the selected codes. The other articles that do not match to any of these codes are employed either with single or special topics such as predictive controlling, or with systematic reviews without focussing on particular methods or applications. Based on this analysis, equipment maintenance appears to be the most important application in the area of PA in SI manufacturing, followed by applications in the area of smart manufacturing and supply chain. From a technology perspective, Big Data is most relevant for PA applications in SI manufacturing followed by ML and Internet of Things.

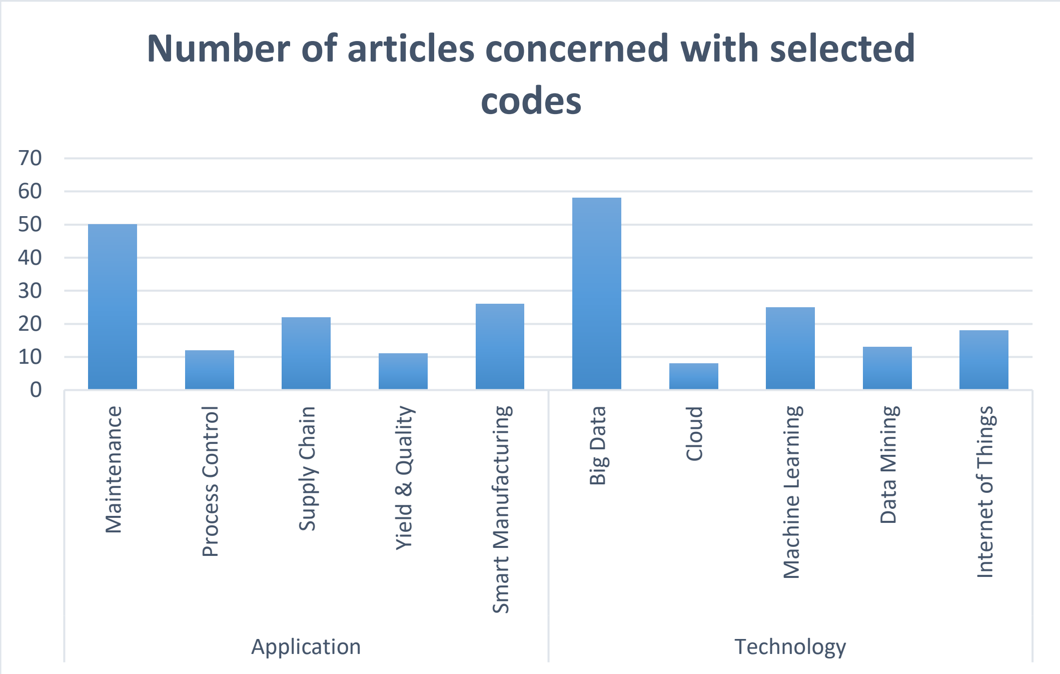


Figure 2-11: Number of Articles concerned with selected Codes

In addition to this analysis, the literature research is conducted to identify further applications where PA methods are used to improve SI manufacturing processes. From this, the following important PA applications in SI manufacturing have been identified:

1. Predictive Maintenance
2. Smart Manufacturing
3. Predictive Process Control
4. Predictive Quality
5. Predictive Dispatching and Scheduling

These applications are discussed in more detail in the following sub-sections. However, PA applications for supply chain purposes are excluded from this study. The reason for this decision is that the thesis focuses on the core manufacturing aspects from the wafer fabrication (frontend) part of the value chain. This focus is supported by the selection of the case study company, whose German factory concentrates on wafer fabrication.

2.5.2 Predictive Maintenance

SI is one of the most capital-intensive industries with significant capital investment in equipment and, therefore, optimization of equipment performance has received noteworthy attention. SI manufacturing processes constantly generate hundreds of metrology data that can be used to analyse and understand failure patterns and to improve the yield of high quality products (Munirathinam and Ramadoss, 2016). Speaking at the January 2000 ISS, the former Intel Senior Vice President, Michael Splinter stated that one hour of downtime for a critical unit of process equipment could be translated into $100,000 of lost revenue. Hence, in a generic wafer fabrication facility, a downtime reduction of only 1% on the 50 most critical tools can lead to revenue opportunities and cost savings of around $100 million annually. By improving response times and repair times and by predicting the point in time when problems may occur, a reduction of unscheduled downtimes can be achieved (Munirathinam and Ramadoss, 2014).

PdM is seen as a data-driven approach to address these goals, which is agreed by many authors, such as Raoslash et al. (2016), Chiu et al. (2017) and Motaghare et al. (2018) However, they partially disagree in scope and targets of a PdM solution. For instance, Chiu et al. (2017) proposed an agent- and cloud-based PdM system for an entire factory that does not only focus on one single machine, whereas Tiddens et al. (2018) pointed out that each machine requires a time-consuming process to implement a suitable PdM solution. Hence, they proposed a method that supports the selection of suitable machines or components. It was found that this evaluation method does not consider logistics or dynamic aspects that might be affected by the application of PdM. Therefore, the approach is not seen as suitable for SI. Nevertheless, it is agreed that such a type of criteria-based pre-selection is important because maintenance experts as well as data scientists are limited in a company and cannot work on a thousand or more PdM solutions simultaneously. Therefore, it is proposed that PdM should be treated as one of many maintenance strategies that supplement a company's maintenance operations. However, it is not clearly defined in the literature how PdM relates to other maintenance strategies. A comprehensive study by Gackowiec

(2019) compared various classifications of maintenance strategies. Some of these classifications treat PdM as their own strategy along with corrective maintenance (e.g. Wang et al. (2007)), whereas others consider it as part of proactive maintenance (e.g. Sambrekar et al. (2018)). However, Rani et al. (2015) classified PdM as a ‘planned maintenance’ strategy on the same level as proactive maintenance. Gackowiec did not regard that Swanson (2001) discussed a further strategy called ‘aggressive maintenance’ that is beyond traditional maintenance. It attempts to improve the overall equipment operation, which leads to increased equipment lifespan. It is assumed that PdM as a technique can be used to prevent unscheduled downtimes as well as to improve the overall equipment operation.

There is a common understanding in the literature that PdM is based on (big) data and applies PA techniques to gain predictions. Coleman et al. (2017) pointed out that built-in or external sensors of connected machines create the fundamental data for PdM. Through network communication (e.g., by using Wi-Fi or RFID), the data is made available for remote monitoring. Sensor data is enriched by other existing data from ERP or PLC using sophisticated middleware and data management platforms. Though these types of data are crucial, it is believed that an effective PdM solution must provide more than pattern recognition in historical sensor and status data. For this purpose, Bink and Zschech (2017) discussed a further approach that adds information from past maintenance actions to classify whether these actions were more risk-affine or risk-averse. Such findings may support future situations to reduce wrong decisions based on subjective interpretations. Yan et al. (2017) considered unstructured data for PdM such as manufacturing videos or voice signals. They discussed in which way an operator’s behaviour and efficiency could be analysed based on this data. However, they did not reflect the ethical issues that arise with such a type of data acquisition and analysis. To overcome these issues, it is suggested that anonymization procedures should be applied as well as techniques to ensure privacy and data protection. Otherwise, the laws and regulations of many countries and companies may prohibit this type of data collection. A case study from Bink and Zschech (2017) discovered that ML procedures, such as clustering, ANN and SVM, generate the most accurate prediction quality for PdM scenarios.

Compared to statistical methods, these procedures return better results for complex and non-linear associations between a target variable (e.g., remaining useful life) and higher-dimensional equipment state data. Furthermore, Butte et al. (2018) considered deep belief networks, convolutional neural networks, random forest and other ML techniques for PdM. They discovered that single models might be prone to poor predictions in real scenarios, although they gained high validity during tests. They stated that this is due to violations of the underlying production environment. To overcome this issue, they proposed applying so-called super learning, which combines several base learning procedures with a meta-learner that is trained to find the optimal combination of prediction algorithms. It is believed that this approach is valuable especially for volatile manufacturing processes in SI. An approach beyond ML was suggested by Cao et al. (2019) who criticized that DM-based PdM is limited to the prediction of a point in time when a failure may occur. However, these solutions are not capable of identifying the criticality of a failure. They emphasized that this capability is important for creating and applying appropriate maintenance plans. To overcome this issue, they proposed an expert system that consists of a domain ontology to store PdM knowledge, a fuzzy c-means classification to learn the criticality from historical data, and SWRL rules to infer the time and criticality of a future machine failure. This semantic approach is seen as relevant to SI due to the heterogenic machine and process landscape. Knowledge about the criticality of a predicted failure supports an appropriate prioritization of maintenance tasks, which might improve both maintenance operations and production performance. Biebl et al. (2020) proposed an advanced SI-specific approach based on Bayesian Networks. It is capable of predicting the root cause of a failure at an etching tool and to provide recommendations to the EM staff.

PdM is not only relevant to SI, but also for many other industries. Therefore, many software- and analytics-oriented companies provide particular PdM solutions to meet these demands. Figure 2-12 (Scully, 2019) shows the results of a study on the global market for PdM. It expects a growth from $3.3 billion in 2018 to $23.5 billion in 2024. Even if the actual growth is less than this optimistic forecast, the trend underpins the increasing importance of PdM.

As discussed earlier in this sub-section, PdM promises the reduction of unscheduled downtimes, which finally results in monetary benefits for a SI company. Some studies were employed to discover the potential benefits of PdM in more detail. Iskandar et al. (2015) focussed on the financial benefits of PdM for semiconductor manufacturing that are gained by avoiding particular costs. They highlighted cost factors, such as lost production, cost of parts and labour and lost yield. They proposed a calculation model to analyse the impact of false positives on the maintenance operations for a specific PdM configuration. Since the focus was on the optimal configuration of a specific solution instead of PdM as a strategy, the model is not capable of calculating general financial benefits of PdM. In addition, they do not consider other SI PS participants, or in which way PdM affects them.

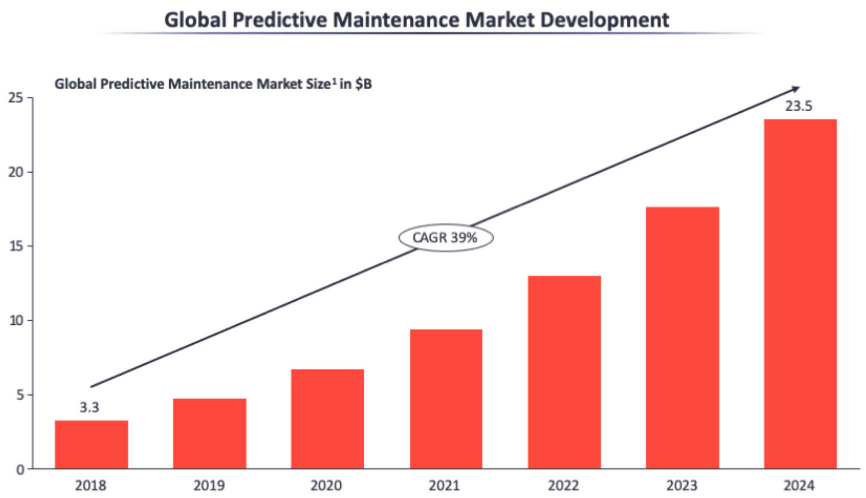


Figure 2-12: Global Market Development and Forecast for PdM (Scully, 2019)

Koitzsch et al. (2012) proposed a model to calculate the potential benefits gained by PdM with a focus on SI wafer fabrication. They preselected expected economic benefits of PdM such as reduction of maintenance costs, increased equipment utilization and reduction of scrap wafers. They found out that PdM generates different benefits for different equipment types, which is an important insight that must be considered before initiating a PdM project. Furthermore, they translated the benefits into financial metrics to state, for instance, how many euros per year could be saved on maintenance costs for a lithography machine. However, the calculation approach shows the following weaknesses:

1) The types of benefits were preselected, so the model is not able to discover other benefits beyond these.
2) The model is concentrated on machine downtimes and does not reflect the effects on PS logistics performance.
3) It is believed that environmental factors were not considered such as available wafers to process, because the article does not discuss them.

A general finding from the literature review is that the benefit evaluation of PdM mostly concentrates on the avoidance of unscheduled machine downtimes and the effects on directly involved PS participants, such as maintenance operations, spare part logistics and avoidance of yield loss. Therefore, it is believed that other benefits or even negative effects could be identified if the scope was increased to logistics aspects, which appear to be the most challenging area in SI value chains as presented in 2.2.4.

2.5.3 Smart Manufacturing

The literature review shows that the term ‘smart manufacturing’ (SM) is not clearly defined. According to Wei et al. (2020), SM refers to a

> manufacturing method that improves its performance with the integrated and intelligent use of processes and resources in cyber, physical, and human spheres to create and deliver products and services, while also collaborating with other domains within an enterprise's value chains (p. 46).

Kang et al. (2016) defined SM as a ‘collection and a paradigm of various technologies that can promote a strategic innovation of the existing manufacturing industry through the convergence of humans, technology, and information’ (p. 111). They highlighted eight key technologies for SM such as internet of things, big data analytics, cyber-physical systems and cloud computing, and the particular features they provide. In contrast, Kusiak

(2018) was less focussed on technologies, but considered SM as a compilation of six pillars: (1) predictive engineering, (2) data, (3) sustainability, (4) manufacturing technology and processes, (5) resource sharing and networking as well as (6) materials. In his opinion, the importance of these pillars 'have been changing, however, they have been around manufacturing throughout its history' (p. 510). However, he saw production planning and forecasting as the predecessors to predictive engineering, which is not agreed because planning and forecasting are logistic core tasks that are still relevant to modern SI PS. Denno et al. (2018) refer to the U.S. National Institute of Standards and Technology which stated that SM systems enable data-driven decisions throughout manufacturing. They pointed out that PA applications in SM systems are most effective where engineers have limited or no understanding of a phenomenon. For phenomena that are understood, conventional analytical models such as operations research generate results that are more accurate. According to Thoben et al. (2017), SM is a technology transfer scheme developed by policy makers and especially known in the United States, Japan and Korea. They considered it as similar to I4.0, which is more prominent in Germany. The goal of this scheme is to support the manufacturing industry in order to upgrade their traditional production facilities to so-called smart factories.

Tao et al. (2018) pointed out that data is a key enabler for SM but it must first be translated into concrete and useful information. This translation requires in-depth knowledge about the data lifecycle in manufacturing that consists of: (1) data source, (2) data collection, (3) data storage, (4) data processing, (5) data visualisation, (6) data transmission and (7) data application. They explained that data applications are able to create value from the data. Beyond PdM, they stated the accurate and rapid translation of customer voices into product features and quality requirements as a possible SM data application. Gao et al. (2020) agreed on the importance of data in the context of smart manufacturing, especially due to the fact of growing data volumes. They highlighted and discussed recent Big Data technologies and PA methods and their value-adding applications in smart factories. Bajic et al. (2018) shared the view that SM is strongly dependent on data. They discussed following ML techniques that are particularly applicable to SM use cases: (1) support vector machine, (2) decision tree, (3) expert system, (4) k-nearest neighbour, (5) naive Bayesian, and (6) artificial neural network. They reviewed and outlined various use cases where these techniques are applied in SM, such as classification problems, pattern recognition and permanent quality improvement, which they see as especially relevant to SI. For benefit evaluation of SM, it is seen as highly important to understand the potential applications behind the overall term, and which process improvements or cost reductions are feasible. However, Bajic et al. (2018) neither clearly presented which PA techniques were applied to which use case, nor which strengths and weaknesses had been discovered. This gap can be closed partially by a study from Wang et al. (2018) who reviewed various deep learning techniques for SM, such as convolutional neural network, deep belief network, autoencoder, and recurrent neural network. They highlighted product quality inspection, machinery fault diagnosis, and defect prognosis as potential applications (where the latter two applications are similar to PdM). The comparison showed, for instance, that deep belief networks could be applied to all types of applications, whereas autoencoder was only applied to machinery fault diagnosis, but is used by most referenced articles.

The literature review indicates that SM itself is not one PA application. However, most of the authors agree that it combines several PA applications to meet various requirements from multiple participants within the value chain. The approach of SM can be understood as extending single PA applications by integrating them seamlessly through central technologies and organizations, and therefore, enabling the creation of synergy effects. Kusiak (2018) expected that increased volume of collected data and the consequently increased prominence of PA methods would drive the future development of SM. However, he pointed out that enterprises must address challenges such as cybersecurity and collaborative standards to gain benefits from this development.

2.5.4 Predictive Process Control

The aim of process control is to actively change a process based on the results of a process monitoring tool. Once an out-of-control situation has been detected, the responsible person applies a change to bring the process back under control. Out-of-control action plans consist of detailed actions that need to be performed in particular situations. Each unique process may be associated with a specific action plan. In addition, advanced process control loops are used to automatically change a process based on the programmed logics and the size of the out-of-control measurement (NIST SEMATECH, 2012).

Moyne et al. (2007) referred to the Semiconductor Equipment and Materials International consortium who considered the following applications for process control: run-to-run (R2R), fault detection and classification (FDC), fault prediction, and statistical process control (SPC). According to Moyne et al. (2000), R2R is a control mechanism that is able to adjust a product recipe autonomously after single machine runs with respect to the particular machine process. By modifying the recipe, the process drift, shift and variability is minimized. Moyne et al. (2016) pointed out that PA methods are mainly relevant to FDC. However, they explained that predicted results from FDC could be used by R2R to improve its performance, for instance, by adjusting the control granularity from lot level to wafer-to-wafer control. SPC is mainly used to identify anomalies using statistical techniques. Though SPC in SI is ‘established as a fundamental technique to improve production efficiency and yield’ (Park et al., 2017, p. 3523), it is suspected that statistical methods do not fit to all types of problems. For this purpose, Khoza and Grobler (2019) compared ML and statistical techniques to predict when a manufacturing process is out of control. They discovered that the random forest algorithm generates better results than other ML methods and that it outperforms the statistical technique Hotelling’s T^2. In addition, Liao et al. (2018) pointed out that ML is a crucial approach for anomaly detection that overcomes the tool and process complexity in SI as well as unknown correlations in sensory data. They proposed a framework based on autoencoder to detect anomalies in real-time for a chemical vapor deposition tool. Despite the valuable insights of these projects, it is doubted that these results can be extrapolated to prove the statement that ML-based process control outperforms SPC in general. Broader research is required to understand and demarcate the optimal use cases for both types of methods.

However, the results indicate that traditional SPC techniques should be questioned in order to improve quality control performance.

FDC is focussed on variations in the process result data to detect anomalies and determine the cause of a fault (Moyne et al., 2007). Figure 2-13 (Tuv et al., 2018) shows an architecture for fault classification that is proposed by and uses technology from Intel. Images of wafer surfaces are collected by metrology equipment and sent to a classification server. The labelled images are returned to a defect analysis database, and in addition, archived to improve the prediction model itself. The solution is also applied at Intel wafer fabrication factories, and delivers benefits such as quicker identification of root causes for specific issues and greater improvement in yield. It uses ML methods such as convolutional neural network for automatic feature learning (Tuv et al., 2018). Furthermore, Lee et al. (2017) demonstrated that convolutional neural networks outperform other ML techniques for FDC, which underpins the importance of this method in this application area.

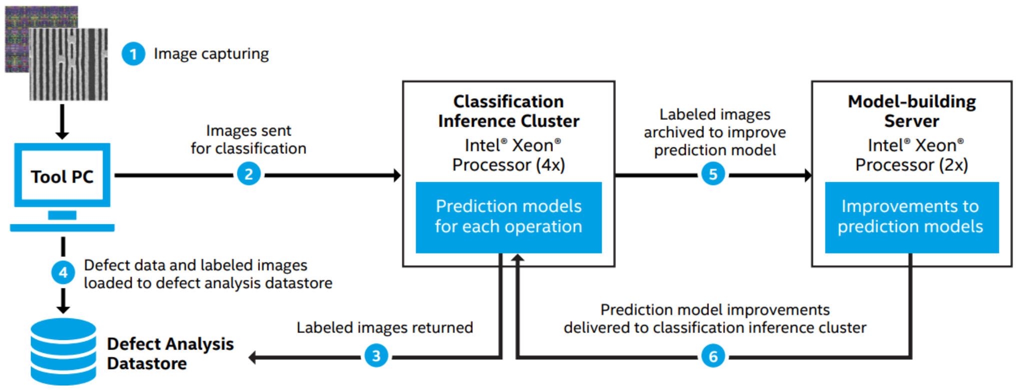


Figure 2-13: Architecture for Automated Defect Classification as proposed by Intel (Tuv et al., 2018, p. 5)

To improve the efficiency of FDC applications, Fan et al. (2020) proposed an approach that uses multiple ML techniques such as k-nearest neighbours and naïve Bayes classifiers. The approach is capable of identifying the key sensors of an equipment and the relevance of their sensor readings regarding quality abnormalities of a wafer. This knowledge enables engineers to focus on particular sensor readings in order to monitor and improve single processes.

Fault prediction also analyses variations in the current process result data, but its purpose is to predict anomalies in future processes (Moyne et al., 2007). In addition to equipment-oriented failure prediction, which has already been discussed as PdM, fault prediction can also be product-oriented and applied to predict wafer or chip defects. Several studies exist that are employed with different goals and aspects of product-oriented fault prediction. Arnold (2016) developed a fault prediction model for wafer and chip defects with random forest classifier, which is a technique based on decision trees. Kim et al. (2019) proposed a deep belief network-based multi-classifier to determine whether a pass/fail test of chips is accurate or not. Kim and Kang (2019) examined the effect of irrelevant variables on the quality of fault prediction results for wafer defects. They did this by testing artificial neural networks, decision trees and k-nearest neighbours and came to the conclusion that decision trees are the most robust against the presence of many irrelevant variables.

General challenges when applying process control in SI include the lack of critical in-situ sensors to provide real-time information on the wafer status, the accurate modelling of electrical parameters, long delays for model updates, the integration of fault detection and classification with R2R, and the existence of inline metrology instead of integrated metrology (Qin et al., 2004). These challenges limit the degree of data quality (e.g., accuracy and topicality) that is required to generate reliable predictions.

2.5.5 Predictive Quality

As discussed in 2.2.1, semiconductor devices are components of various products including goods that are crucial for human safety such as distance sensors in cars. Consequently, the proven quality and reliability of semiconductor devices are highly important. Quality indicates whether, and to which degree, a device performs its proper function. In addition, reliability shows to what extent a device keeps to its original level of quality over time and against various conditions (Crossley, 2008). Yang et al. (2003) concluded that quality management practices are also crucial to on-time delivery performance in SI. However, a number of issues hinders the successful application of these practices, such as the limited role of the quality department, a lack of established techniques to improve the design quality, and insufficient process management capabilities.

Certainly, reduced equipment and process faults (as discussed in 2.5.2 and 2.5.4) have a positive influence on the quality of produced goods. Studies by Lee et al. (2019), Critical Manufacturing (2017) and Besnard et al. (2012) agreed with this hypothesis and treat the term ‘predictive quality’ (PQ) as a result of PdM or process control.

However, this sort of PQ considers only the manufacturing process and ignores the preceding stages of the value chain. Following the ‘quality-by-design’ approach, the quality of a product is influenced by several factors beyond the physical production. Prior to the design of a proper manufacturing process, development engineers must at least specify a quantifiable target quality profile and critical material quality attributes (Lionberger et al., 2008). Henning (2018) considered this perspective and defined PQ as the prediction of properties that are relevant to the quality of a certain product based on data that is gathered from the use of this product. The goal of a PQ assurance concept, as shown in Figure 2-14, is to ensure product quality in advance before faulty products can be manufactured. For this purpose, data from customer returns, quality inspections or product specifications are collected. ML algorithms are trained to identify different types of product failures based on collected product or production process characteristics. An integrated assistance system is able to propose alternative product characteristics that would improve the quality at most. Development and design engineers can use these proposals to modify the product specifications accordingly as input to the future manufacturing process.

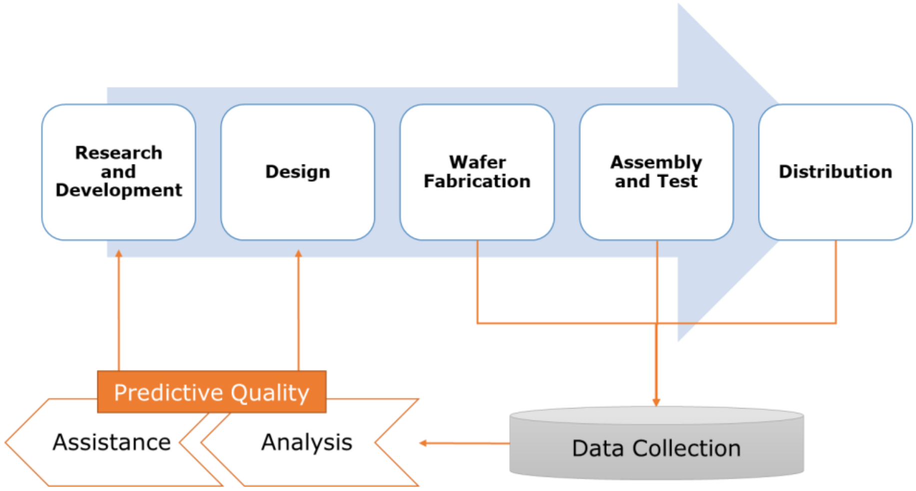


Figure 2-14: PQ Assurance Concept inspired by Henning (2018)

The reduction of time and costs for device testing can be seen as another goal of product-oriented PQ. Schellenberger (2018) pointed out that the various process steps for quality control produce up to 50% of the total costs of a chip. At the end of the frontend stage in the SI value chain, typically 100% of chips on a wafer are tested via probing procedures. These procedures are time-consuming and expensive because a machine must test each wafer chip by chip – this means that the more chips that are on a wafer, the more time is required for probing. The approach of predictive probing considers only a selected number of chips (~7%) and decreases the processing time significantly. To achieve the same result as for full probing, relevant historical data from upstream measurements and other control procedures is collected and analysed using a convolutional neural network (Schellenberger, 2018). Figure 2-15 visualises the approach for chips on a wafer, where the blue squares indicate the chips to be measured for both full and predictive probing. The study concludes that both approaches generate the same result (e.g., classified pass or fail chips), but with different probing efforts. It is agreed that this way of probing would gain significant benefits to SI companies in terms of lead time and cost reduction.

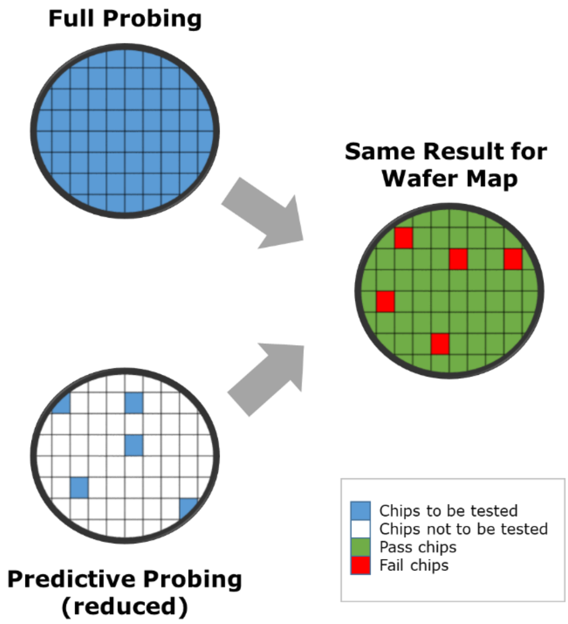


Figure 2-15: Predictive Probing inspired by Schellenberger (2018)

A similar approach was proposed by Schmitt et al. (2020) in order to reduce the quality inspection efforts. They combined ML techniques with cloud and edge computing technologies and conducted a case study at a surface mount technology factory that confirmed the effectivity of this new approach. Stich et al. (2020) pointed out that yield prediction is a critical and complex issue in the SI. Based on the process capabilities of single process steps, the recipe, the current machine state and manufacturing history of the individual wafer, they apply ML techniques to generate improved yield indicators. Lyu et al. (2020) provided a more advanced approach that is capable of identifying the root causes of product defects. They used the features of Internet-of-Things to efficiently collect manufacturing data and applied statistical techniques as well as decision trees to generate rules that detect those parameters in the manufacturing process that cause product defects. A case study showed a defect rate that decreased from 20% to 5%.

Beyond product quality, reliability prediction requires an understanding of the time-to-failure behaviour of a semiconductor device. To gain this understanding, data about the device structure and chemistry, manufacturing process, packaging material and operational conditions must be considered (Xie and Pecht, 2003). Thaduri et al. (2013) proposed a reliability prediction model that combines the strengths of the Physics of Failures method and PA methods such as regression and SVM. The model suggests different alternatives for enhancement in reliability and supports the reduction in recall or replacement costs. Huang et al. (2016) developed a narrow-cut prediction model to understand and improve degradation processes. These insights allow engineers to increase the reliability of avalanche photodiodes that are used in datacenters, wireless or cloud computing networks.

Generally, the reviewed literature does not use a common definition of PQ. Most of the articles are concerned with quality improvement by avoiding incidents during the manufacturing process, and have a significant overlap to the approaches of PdM and process control. Sub-section 2.5.5 emphasises PQ approaches beyond those applications.

2.5.6 Predictive Dispatching and Scheduling

A special characteristic in semiconductor wafer fabrication compared to other industries is that wafers are produced in layers. Each layer is created and modified through various process steps. As pointed out by Varadarajan and Sarin (2006), the machines that are required to perform these process steps are expensive, hence, only a limited number of the same type of machine is available in a factory. Most probably, one wafer revisits a machine multiple times with different recipe requirements until the final layer is finished. In addition to this machine capacity limitation, a wafer fabrication process for one product may consist of around 600 single steps and a factory serves around 200 products simultaneously. Furthermore, the machine types and process steps differ significantly from each other in terms of batch versus serial processing, process duration and sequence-dependent setups (Varadarajan and Sarin, 2006). To cope with this situation, advanced software tools are applied for scheduling and dispatching. At the detailed level, these tools dictate to production staff or transportation robots in real-time the production lot that has to be moved to a particular machine to perform a certain process step. Such tools provide rule-based dispatching, real-time reporting as well as data integration with a manufacturing execution system and other IT systems. The expected benefits are up to 15% increased wafer output per day, 50% reduction in cycle time and cycle time variability as well as up to 10% increased equipment utilization (Applied Materials, n.d.).

To understand the differences between scheduling and dispatching in manufacturing, McKay and Wiers (2003) considered the following aspects: (1) horizon and timing, (2) decision making, and (3) context. It was established that dispatching is measured from minutes to days and decisions are executed continuously each day, whereas scheduling typically constructs a production schedule once a week. Scheduling orchestrates the resource allocation and manipulates demand, whereas dispatching is responsible for immediate decisions based on setup, job duration and resource availability. Generally, dispatching tools are highly interacting with production staff, whereas scheduling tools are used by planning experts. This classification is reasonable and fits with observations at real SI companies.

Several studies explore the opportunities to improve the quality of scheduling and dispatching results by the application of PA methods. Rothe et al. (2014) highlighted the influence of inefficient carrier logistics on the equipment utilization and factory throughput. Challenges in this type of logistics include the carrier exchange performance, changing lot sizes, different equipment configurations and internal equipment buffers. The study applied PA for different targets, for instance, to predict the readiness to unload a carrier from a piece of equipment, to predict material starvation of equipment load ports, and to predict the carrier dispatch behaviour ahead of time. Following the study conclusions, this type of predictive dispatching overcomes most of the inefficiencies of typical carrier logistics. Kuhnle et al. (2019) proposed an autonomous order dispatching agent based on reinforcement-learning. This approach is intended to overcome the challenges in semiconductor manufacturing, such as dynamic and non-deterministic production environments and unexpected incidents. Traditional methods (e.g., mathematical programming, heuristics and dispatching rules) are not considered appropriate to meet these challenges. The study presented a comparison of the throughput times for agent-based and heuristic-based dispatching under changing buffer capacities. Based on a real-world use case, the agent-based approach achieved better overall results. Zahmani et al. (2015) applied decision trees to generate new dispatch rules for a single machine. To solve the dispatch rules, they use a genetic algorithm.

Yu et al. (2020) recommended a prediction-based dynamic scheduling method with a multi-layer perceptron for load balancing. Compared to traditional scheduling methods, the predictive approach shows improvements in daily movement, equipment utilization, throughput rate and cycle time. A study by Takeda Berger et al. (2019) applied ML techniques in combination with simulation-based optimization for predictive-reactive production scheduling (PRPS). Figure 2-16 (Takeda Berger et al., 2019) shows a schematic of this PRPS approach. The PRPS system is based on data from the nominal factory scheduling. The predictive scheduling component analyses historical data regarding disruptions related to inventory that were not considered by the nominal scheduling. If required, the component modifies the schedule to eliminate these disruptions. Operational data, which is related to production interruptions, is continuously gathered and stored. If the PRPS system detects any problems, it verifies if the current schedule is affected. If so, the reactive scheduling component is triggered. The ML sub-component collects online data form the shop floor and generates a solution. During the calculation, the simulation sub-component provides partial solutions to the production execution.

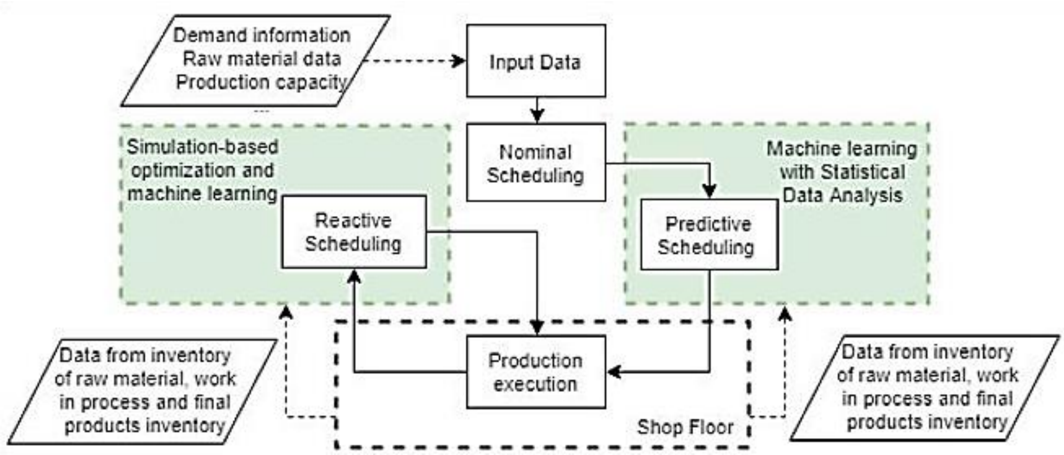


Figure 2-16: Schematic of Predictive-reactive Scheduling (Takeda Berger et al., 2019, p. 1346)

Particularly in the area of predictive scheduling, the literature review has discovered a significant number of articles that call their approach ‘predictive’ without applying PA as considered in this thesis context. To gain predictions, most of the authors apply analytical, stochastic or deterministic techniques instead, for example, Nouiri et al. (2019), Ali Abuhasel (2016) and Lou et al. (2012). These approaches are not in the scope of this thesis, and hence, not discussed in more detail.

2.6 Conceptual Framework

The previous sections 2.2 to 2.5 discussed PA and SI mostly independent from each other. The PA applications that are relevant to semiconductor manufacturing have been discussed regarding their particular benefits and challenges. However, as the foundation of this research project, a conceptual framework is required to associate challenges in SI value chains to PA applications.

2.6.1 Existing Frameworks

Various articles have been reviewed to examine proposed frameworks and to understand to what extent they fit into this research project. Moyne and Iskandar (2017) discussed challenges in SI that prohibit the proper usage of PA methods and applications. However, they focussed on challenges regarding the applicability of PA rather than on how PA supports overcoming challenges in the value chain. Ren et al. (2019) proposed a conceptual framework of big data analytics in sustainable smart manufacturing systems. They focussed on product lifecycle management and considered the way big data analytics can help to improve single steps of the lifecycle. Ivanov et al. (2019) examined the influence of digital technologies and Industry 4.0 on supply chain disruption risks. The conceptual framework developed by Kozjek et al. (2020) intends to facilitate the introduction of big data analytics in manufacturing systems. It provides a domain model with different levels of abstraction and a reference procedure for development and implementation of a PA application. Lee et al. (2013) provided a conceptual framework that describes a so-called predictive manufacturing system. It associates data sources, data types, big data technologies, enterprise IT systems and target applications, such as PdM and overall equipment efficiency. Belhadi et al. (2019) proposed a framework that associates manufacturing process challenges via big data analytics faculties with values gained by PA. The challenges, however, are not SI-specific but more general (e.g., safety and risk analysis).

The review shows that none of the proposed frameworks is suited to this research project. Apart from Moyne and Iskandar (2017), none of the frameworks is employed with SI in particular. Therefore, the industry-specific challenges that have been discussed in 2.2.4 are not considered. Some frameworks are focussed on either PA or big data technologies and do not sufficiently consider the influences on value chains. Other frameworks consider such influences, but concentrate on supply chain or product lifecycle management and not on manufacturing aspects. These findings indicate a gap in the literature that is addressed by this thesis.

2.6.2 Proposal of a New Framework

A new conceptual framework based on the preceding literature study is proposed and presented in Figure 2-17. The framework consists of four sections from the bottom up: (1) SI value chain, (2) SI value chain challenges, (3) PA applications and (4) PA methods. Hence, it connects the two major areas in this thesis: PA (top part) and SI (bottom part). In section (1), the SI value chain with its main stages is presented. Because it is the primary focus of this thesis, the wafer fabrication stage is highlighted. The challenges of SI value chains previously discussed are shown in section (2). These are primarily valid for the wafer fabrication process, but are also related to RnD as well as product design. The framework connects those challenges that are suspected of having a logical dependency. For instance, the importance of capacity, or the necessity of high utilization are only relevant because semiconductor equipment is expensive. Another example is that the positive development of yield over time is a result of highly variable processes that are less controlled at the beginning of the lifecycle of a newly released semiconductor device.

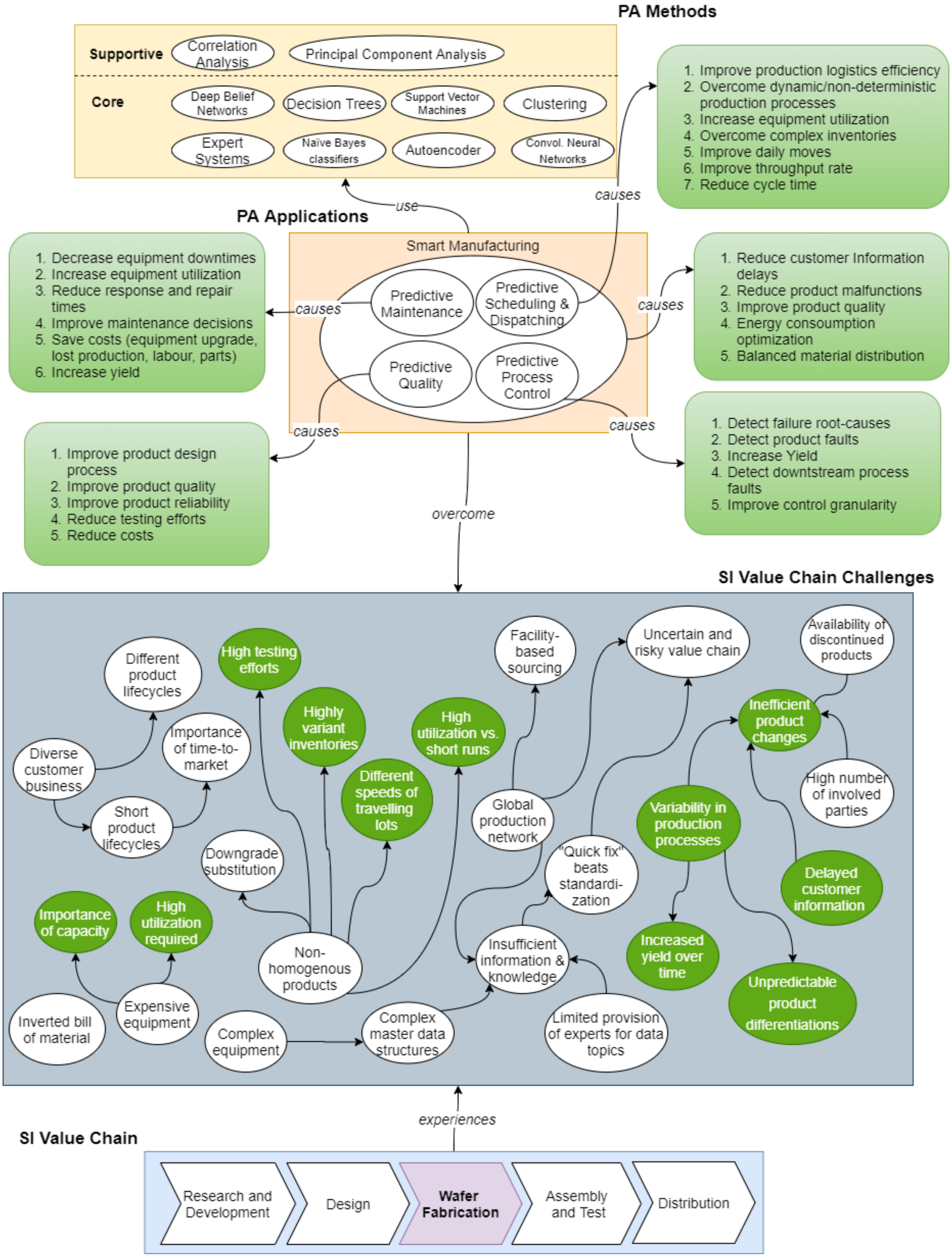


Figure 2-17: Conceptual Framework for this Thesis

Section (3) presents the discussed PA applications that are relevant for semiconductor manufacturing. As explained in 2.5.3, smart manufacturing is considered as a collection of multiple and partially integrated PA applications. Therefore, it visually consists of the other presented PA applications. Section

(4) presents selected PA methods that are relevant to the presented PA applications. They are divided into supportive and core as suggested in 2.4.

It should be highlighted that this list is not complete and more relevant methods may exist. However, these are the ones that have been proved to be crucial for the particular PA applications. Generally, all PA applications can use the full set of PA methods, although some studies recommend particular methods for certain applications.

As discussed in 2.5, each PA application is expected to cause various benefits that are listed in green boxes and are associated with the corresponding application. Considering these benefits, the framework suggests that particular challenges in SI value chains can be overcome by PA applications. The challenges in section (2) that could potentially be mastered by PA are highlighted in green. An exemplary relation exists between the increased equipment utilization gained by predictive dispatching that would directly meet the challenge where high utilization is required due to significant equipment expense. Another benefit that directly masters a challenge is the reduced customer information delay that could be achieved by smart manufacturing. Other challenges are only influenced indirectly, e.g., the variability in production processes could be reduced potentially by the application of predictive process control, which supports the root-cause detection of faults, and therefore enables the improvement of the process steps towards higher process stability. However, these types of indirect relationships must be discovered and proven through a scientific approach.

In particular, the influences of PA on the various performance aspects of a SI PS are not clear from the literature study. Hence, it is believed that unknown transitive or even contradictory influences of PA applications on SI value chains can be discovered based on various causal relationships in a SI PS (hypothesis 1). In addition, it is believed that the potential benefits of PA are dependent on specific scenarios. This would mean that the value chain benefits of the same PA application are variable, for instance, between different workcenters or different operations (hypothesis 2). A deeper understanding of these assertions would support production managers and engineers to overcome the discussed challenges in SI value chains by implementing a PA application under consideration of transitive effects. The thesis tests these hypotheses by applying a research methodology that is presented in Chapter 3.

Finally yet importantly, the framework suggests that there are challenges in SI value chains that cannot be overcome by applying the presented PA applications. Such challenges are, for instance, the inverted bill of materials, the short product lifecycles, and complex master data structures. The investigation of which methods would master these challenges is out of the scope of this research project.

2.7 Summary and Importance of This Thesis

This chapter has presented the literature review. Since this thesis is employed with the implications of PA on SI PS performance, the chapter firstly considered SI and PA independently before particular PA applications for semiconductor manufacturing were reviewed.

With regard to SI, the chapter has presented the literature review in the following areas: history and industry overview, optoelectronic industry, SI value chains and particular challenges in semiconductor manufacturing. The Following key issues could be identified from **SI-related** literature:

- The historical development of SI was not commonly defined. Therefore, a separation into three historical perspectives was proposed: semiconductor technology, semiconductor-based applications, and the industrial development of the semiconductor market.
- SI is diverse and separated by business models that differ significantly from each other in scope and economic profit. To evaluate meaningful benefits of PA, it is suggested that a particular area is focussed on, which is the wafer fabrication.
- The Covid-19 pandemic has had a negative impact on the economic profit in 2020; however, recent trends suggest that the previously forecasted positive trend is expected to continue.
- Though SI value chains are globally distributed, they are geographically concentrated. Possible implications of the Covid-19

pandemic on this type of value chain design were criticized as not being economical.

- SI value chains are complex and differ from value chains in other businesses. It was suggested that Porter's established value chain model does not meet the requirements of SI. Hence, an alternative model was proposed that covers the primary activities.
- Most manufacturing-related challenges in SI value chains are associated with logistics. However, it is believed that these challenges are mostly driven by challenges in other areas such as product management and engineering because of volatile market situations, diverse product lifecycles and variability in single processes.
- SI suffers from a lack of standardization in data and IT solutions caused by urgent operational needs that lead to 'quick fixes' instead of sustainable solutions. It is believed that this issue reinforces challenges in other areas, because solutions are isolated, area-specific IT systems are not integrated sufficiently, and the risk of data inconsistency increases.

The area of PA has been employed with the definition and overview of PA in general and with associated relevant methods. The Following key issues could be identified from **PA-related** literature:

- The importance of PA has increased significantly over recent years, though the term is not clearly defined by the literatures. Several explanations for this development have been proposed, for instance, the relation to other technological trends in the area of manufacturing.
- PA did not provide fundamental contributions to science as it only reuses previously existing methods from statistics or ML. Therefore, it is seen as valid to call it a buzzword.
- A demarcation between PA and DM is not necessary since both terms apply the same type of methods to overcome similar problems. However, it can be stated that PA mainly considers the predictive parts of DM, whereas DM is also concerned with finding new relationships in large amounts of data.
- A demarcation between PA and other types of analytics is useful to address the goals and expectations of a PA application. However, it

showed that the term ‘analytics’ overlaps with other disciplines such as artificial intelligence.

- Relevant methods for PA could not be clearly associated due to the inconsistent definition of PA itself. To overcome this challenge, it was proposed to divide the methods into supportive and core while considering both as integral parts of a PA solution. Furthermore, particular PA core methods were mentioned in the context of PA applications.
- Due to the inconsistent definition of PA and the variety of methods, it is not likely that a benefit calculation on this broad level would generate meaningful results.
- It was further concluded that a benefit evaluation is not possible for single predictive techniques since their selection depends on the specific problem statement, given dataset and type of data preparation. Instead, it was proposed to identify PA applications that gained attention in the literature and that could be applied to master challenges in SI value chains. By analysing in which way these PA applications would improve business processes, it is expected to be able to calculate particular benefits.

In order to discover possible areas for benefit evaluation in semiconductor manufacturing, the following PA applications have been identified and critically reviewed: PdM, SM, predictive process control, PQ, as well as predictive dispatching and scheduling. The Following key issues could be identified for **PdM**:

- Though PdM as a term has been established for many years, the scope and targets of a PdM solution are not commonly defined by the literature. Nevertheless, a positive economic trend is forecasted beyond SI that underpins the importance of predictive capabilities to reduce equipment downtimes.
- PdM is not clearly related to other maintenance strategies; to gain a clear understanding in this thesis, it was proposed to treat PdM as a technique for both preventive and aggressive maintenance that supplements other strategies.

- Existing studies on the selection of suitable machines for PdM did not consider logistics aspects, though these were identified as the most challenging in semiconductor manufacturing.
- Existing studies on benefit calculation for PdM show various weaknesses, especially the missing consideration of influences on logistics.

The Following key issues could be identified for **SM**:

- The term SM was not clearly defined in the literature and showed the characteristics of a buzzword.
- Several applications that were referred to SM showed significant overlaps with PdM or process control. Therefore, it could be implied that SM itself is not one PA application, but combines several PA applications to meet various requirements from multiple participants within the value chain.
- Benefits from SM can only be generated if it is built on collaborative standards. Since standardization was identified as a weak point in SI value chains, the implementation and utilization of SM in SI is seen as risky and challenging.

The Following key issues could be identified for **predictive process control**:

- R2R is not directly relevant to PA; however, it could benefit indirectly from PA methods that are applied to improve FDC results.
- SPC was found to be an established approach in SI using statistical techniques. Though experiments suggest that ML generates better results for anomaly detection, it was not evident from the literature if there is a trend in SI to replace traditional SPC by ML-based solutions.
- FDC appeared to be commonly defined. Studies were employed to identify optimal architectures and methods by which convolutional neural networks were identified to outperform other ML techniques.
- Fault prediction showed an overlap with PdM. To overcome this issue, it was divided into equipment-oriented and product-oriented fault prediction. The latter one is capable of predicting wafer or chip defects.

- Generally, the implications that PA applications in the area of process control have on the logistics performance of an SI PS were not studied.

The Following key issues could be identified for **PQ**:

- The term PQ was not commonly defined. Furthermore, the majority of the literature considered PQ as a result from PdM. Nevertheless, the review revealed applications beyond this limited view.
- The differentiation between quality and reliability in order to gain realistic expectations from a PQ application was highlighted. Indeed, it was found that the studies on both types of PQ differ in scope and applicability.
- PQ could be applied to gain quality by design. However, such a PQ solution involves and connects several stages in the value. Similar to SM, this type of integration is seen as a challenging venture due to the lack of standardization in SI. Nonetheless, it is expected that increased quality by design would lead to positive implications for the PS performance due to increased stability of single processes and reduced rework rates.
- Predictive probing was identified to be a promising solution in order to reduce testing efforts and to keep testing quality of full probing at the same time. Reduced testing efforts might have a positive impact on the PS performances, however, this type of implication was not studied so far.
- Reliability-oriented PQ appeared to be mainly important to gain a reduction in recall or replacement costs. Though manufacturing data is part of the source dataset for PA, they are not considered to have influence on the SI PS performance.

The Following key issues could be identified for **predictive dispatching and scheduling**:

- The review showed that scheduling and dispatching refer to different scopes and targets. Thus, it is important to differentiate related predictive solutions in order to discover realistic implications on the PS performance.

- PA showed significant improvements for various dispatching use cases. Since established dispatching tools mostly apply rule-based or analytical approaches, it can be seen that there are opportunities to improve SI PS performance by applying PA.
- In addition, the application of ML for scheduling purposes was proved to outperform traditional approaches, which is also expected to improve logistics performance. However, it was found that approaches are often called ‘predictive’ without applying PA as considered in this thesis context. Therefore, future research regarding benefits in this area must consider an appropriate demarcation.

The various issues that have been detected from the reviewed areas underpin the relevance and importance of this thesis that is employed with the impacts of PA on SI PS performance. In particular, the following arguments support its importance:

- Special challenges exist in SI that differ from other industries. Therefore, it seen as important to study in particular the implications of PA on the SI.
- None of the frameworks from reviewed articles considered implications of PA to overcome challenges in SI value chains.
- Logistics was identified to be the most challenging area in SI PS, however, it was not studied previously in which way PdM would affect logistics performance.
- There is growing attention on PA and PdM in particular that is forecasted to continue over the upcoming years. This trend was also verified for SI. Therefore, the results from this thesis are expected to gain further attention in future.
- PA and PdM were not clearly defined in the literature. It is expected that the results from the benefit analysis and evaluation in this thesis will help future researchers to narrow down the scope for PdM in SI.
- Selecting suitable machines for PdM was identified to be an important capability, since this approach can only be applied to a limited number

of machines due to the time-consuming implementation process. However, existing approaches did not consider logistic aspects, which are explicitly examined by this thesis.

- Implications of predictive process control and PQ on SI PS performance have not been studied previously. Though these applications are not particularly considered in this project, they are seen as important for future work that can build on the models from this thesis.

Finally, a conceptual framework has been proposed that supports this study. The results of this chapter indicate a gap in the literature that is addressed by this thesis.

Chapter 3 Research Methodology and Design

3.1 Research Methodology

The development of a research methodology is a process that covers several phases. Figure 3-1 provides a comprehensive overview of these phases. The development process starts at the outer layer that addresses the selection of an appropriate research philosophy. Then, the most appropriate approach and strategies must be identified. Afterwards, the researcher must define the choices, the time horizon plus techniques and procedures for data collection and analysis.

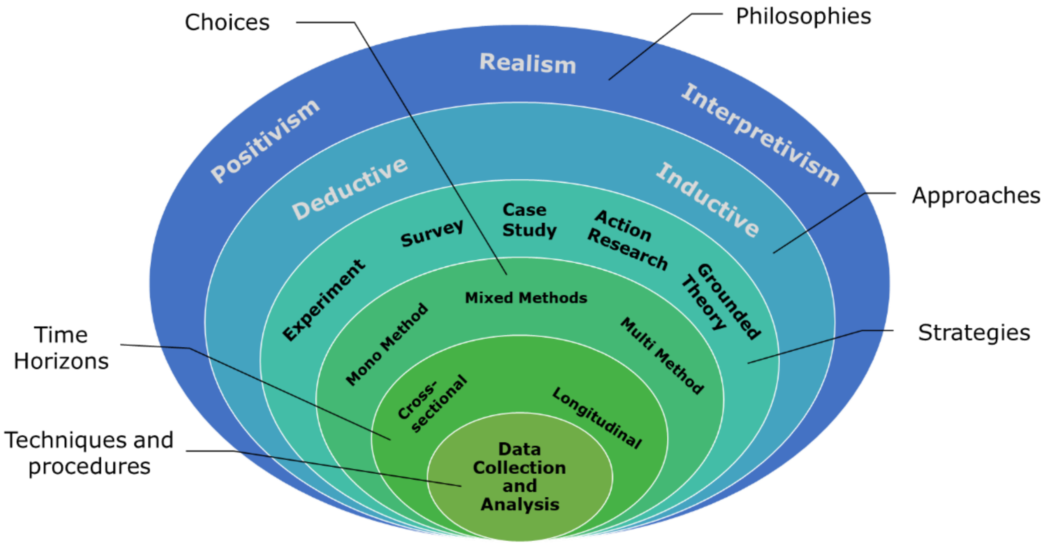


Figure 3-1: Research Onion inspired by Saunders et al. (2009)

The following sub-sections discuss each phase in order to develop the research methodology for this thesis.

3.1.1 Research Philosophy

A research philosophy refers to a system of beliefs and assumptions about the development of knowledge. The selected philosophy underpins the methodological choice, research strategy as well as data collection techniques and analysis procedures. These aspects support the planning of a coherent research project (Saunders et al., 2009).

According to Galliers (1991), there are two major research philosophies, which are positivist (or scientific) and interpretive. Positivist research is characterised by repeatability, reductionism and refutability. In addition, it is assumed that phenomena under study can be observed objectively and rigorously. In contrast, interpretive research considers many different interpretations of social phenomena as well as the impact of the researcher on the social system under investigation. Jeffery (1993) concluded that interpretivism is a necessary approach for 'areas in which social activities make up a significant component of the process problem type' (p. 115). Examples for these areas are the specification of requirements, project management or user relationships. Positivism is considered to support research projects that have a high technical component and lower social component, e.g. those projects with the aim of re-engineering decisions. Table 3-1 shows a comparison of the crucial characteristics of positivism, which are also valid for post-positivism, and interpretivism.

Table 3-1: Comparison of Research Paradigms based on Chilisa (2012)

Characteristic	**Positivism / Post-Positivism**	**Interpretivism**
Reason for doing the research	To discover laws that are generalizable and govern the universe	To understand and describe human nature
Philosophical underpinnings	Informed mainly by realism, idealism and critical realism	Informed by hermeneutics and phenomenology
Ontological assumptions	One reality, knowable within probability	Multiple socially constructed realties
Place of values in the research process	Science is value free, and values have no place except when choosing a topic	Values are an integral part of social life; no group's values are wrong, only different
Nature of knowledge	Objective	Subjective; idiographic
What counts as truth	Based on precise observation and measurement that is verifiable	Truth is context dependent
Methodology	Quantitative; correlational; quasi-experimental; experimental; causal comparative; survey	Qualitative; phenomenology; ethnographic; symbolic interaction; naturalistic
Techniques of gathering data	Mainly questionnaires, observation, tests and experiments	Mainly interviews, participant observation, pictures, photographs, diaries and documents

The characteristics of this research project are similar to those of positivism and post-positivism. The project discovers generalizable laws that support decision-making in SI manufacturing regarding PA and considers SI as one reality that is known to some extent. The research suggests that truth is based on the precise observation of the subject matter by experts, and measurement via IT-integrated manufacturing processes. However, the research is concerned with questions that can only be answered with specific probability instead of absolute certainty. Furthermore, the research project constructs new knowledge instead of passively noting laws of nature. These characteristics indicate that post-positivism fits better to this research compared to positivism (Crotty, 2015). Botha et al. (2012) considered the following aspects in order to identify the correct paradigm: ontology ("What do we believe about the nature of reality?"), epistemology ("How do we know what we know?") and axiology ("what do we believe is true"). From an ontological viewpoint, it is believed that the researcher can only discover the reality within a certain area of probability due to human limitations. From an epistemological position, perfect objectivity is not believed to be achievable. The axiological viewpoint is that the researcher is not value-free and neutral in this project and that his personal and professional background influences the outcome of what is observed. Therefore, these assessments support the conclusion that post-positivism is the appropriate paradigm for this thesis.

3.1.2 Research Approach

The research approach sets the starting point and direction of a research project. Bryman and Bell (2015) discussed three research approaches: deductive, inductive and abductive. They explained that the main distinctive point between induction and deduction is the relevance of hypothesis to the study. A deductive approach tests whether or not the hypothesis is valid, whereas the inductive approach supports the creation of new theories and generalisations. The abductive approach produces explanations for 'surprising facts' or 'puzzles' that are known at the beginning of the study. According to Saunders et al. (2009), deduction starts with a theory that is developed from the literature review results. In contrast, induction starts with the collection of data to explore a phenomenon to generate or build a theory.

The third approach, abduction, starts with data collection to explore a phenomenon in order to identify themes and to explain patterns. Abductive research intends to generate a new, or to modify, an existing theory that is tested by additional data collection. Collis and Hussey (2014) specified the characteristics of deduction and induction in more detail. They stated that deductive research requires the development of a conceptual or theoretical framework, which is then tested by empirical observation. Particular instances are deduced from general inferences, for which reason deduction is seen as moving from the general to the particular. With inductive research, theory is developed from the observation of empirical reality. This means that general inferences are induced from particular instances and this is why induction is seen as moving from the particular to the general. Figure 3-2 visualises the different directions of both research approaches.

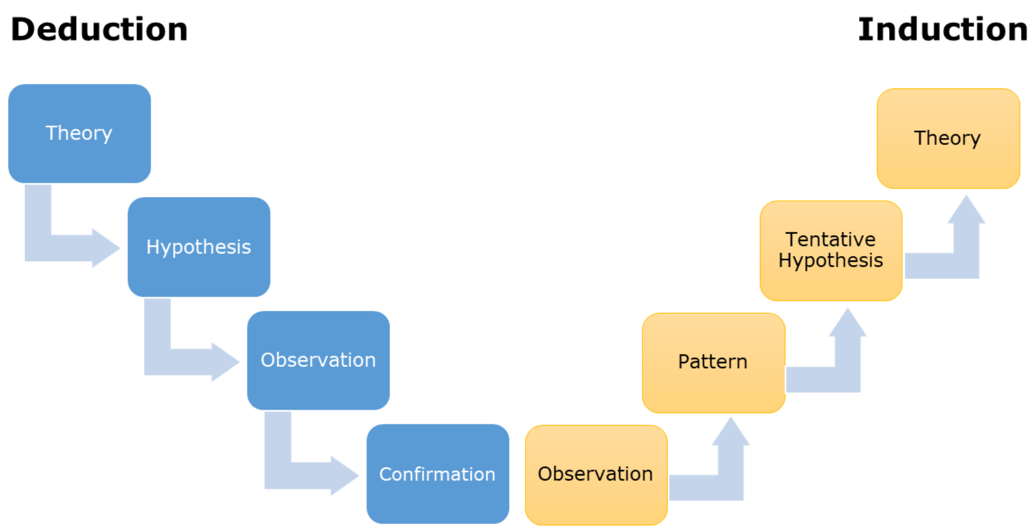


Figure 3-2: Comparison of Deductive and Inductive Approach adapted from Burney and Saleem (2008)

The appropriate approach for this thesis is deductive research. It starts with the development of a conceptual framework that associates theories of PA and SI value chains. The aim of the research project is to explore the benefits of PA in SI in detail, as it is assumed that the benefits vary depending on environmental factors. An additional aim is to identify the transitive impacts of PA on various aspects of SI manufacturing and to compare the potential benefits when applying PA to different workcenters and operations. Furthermore, the thesis intends to gain new insights when PA applications have only limited benefits, or may even contribute to the deterioration in production performance. For this purpose, observations at a real SI company are required to collect data. After several steps of data analysis, modelling and simulation, the hypotheses can be either confirmed or rejected.

3.1.3 Research Strategies

The aim of research strategies is to determine the method of gathering data for a thesis. Galliers (1991) compiled methods that positivist researchers in the area of information systems have selected and applied in their studies. As shown in Table 3-1, the techniques for data collection and the general methodology are valid for both positivism and post-positivism. Therefore, these methods are considered to be valid for this thesis as well. From the overall set of methods, Table 3-2 lists and describes the ones that have been applied in this research.

Table 3-2: Crucial Methods for Data Collection in Positivist Research based on Galliers (1991, pp. 333–336)

Method	Characteristics
Case studies	• Application to real world situations • Enables the capture of reality in greater detail than the previously listed methods • Results in a greater number of variables that can be considered for analysis • Usually restricted to a single event or organisation • Difficulty exists to acquire a statistically meaningful number of similar organisations; therefore, limited ability to build generalisations • Limited control of variables under study and hence limited differentiation between causes and effects • Different interpretations may exist on observations by stakeholders or researcher
Theorem Proof	• Enables the identification of application areas from fields such as computer science; other methods were not able to capture these areas • Strengths of the method are its repeatability, reductionism and refutability, as well as the precision of results • Limited applicability in positivist research because researchers move towards the social pole of the socio-technical spectrum
Simulation	• Applicable to problems that are difficult or impossible to solve by analytical methods • Behaviours of the system under study are copied by generating appropriate random variables • Same limitations as for experimental methods e.g., no consideration of excluded variables that exist in the real-world system

Each of the methods has its strengths and weaknesses. A researcher must select a method in order to gather suitable data to solve the particular research objectives. Based on the characteristics and goals of this study, the selected methods have been applied for the following targets:

- Case study
  - To gather primary data from real world observations related to the hypotheses from the conceptual framework
  - To gather secondary data from internal company documents
- Theorem proof (through ontology and first-order logic)
  - To test hypotheses qualitatively through logical inference
  - To provide a simple adoptable method for other researchers and SI manufacturing experts that enables them to understand the direct and transitive impacts of PA on SI PS
- Simulation (through SD)
  - To test hypotheses quantitatively through dynamic simulation of SI PS behaviours
  - To provide a reproducible method to other researchers and SI manufacturing experts that enables them to explore workcenter- and operation-specific benefits of PA applications

Another strength of case study is that it allows the understanding of dynamics present within single settings (Eisenhardt, 1989). According to Harrison et al. (2017), case study as a method is not associated with a specific philosophical orientation, but it can be applied to multiple perspectives, such as realism, positivism, relativism or interpretivism. Table 3-3 shows the key elements and their descriptors of case study research.

As an additional strategy, the literature review is applied to narrow down and connect the areas that are relevant to this research project. This is an important prerequisite for stating the research objectives. The review process is designed as follows (Guthrie, 2010):

1. Analysing literature
2. Evaluating its relevance
3. Creating a conceptual framework.

Table 3-3: Case Study Elements and Descriptors adapted from Harrison

Element	Description
The case	• Object of the case study identified as the entity of interest or unit of analysis • Program, individual, group, social situation, organization, event, phenomena, or process
A bounded system	• Bounded by time, space, and activity • Encompasses a system of connections • Bounding applies frames to manage contextual variables • Boundaries between the case and context can be blurred
Studied in context	• Studied in its real life setting or natural environment • Context is significant to understanding the case • Contextual variables include political, economic, social, cultural, historical, and/or organizational factors
In-depth study	• Chosen for intensive analysis of an issue • Fieldwork is intrinsic to the process of the inquiry • Subjectivity a consistent thread—varies in depth and engagement depending on the philosophical orientation of the research, purpose, and methods • Reflexive techniques pivotal to credibility and research process
Selecting the case	• Based on the purpose and conditions of the study • Involves decisions about people, settings, events, phenomena, social processes • Scope: single, within case and multiple case sampling • Broad: capture ordinary, unique, varied and/or accessible aspects • Methods: specified criteria, methodical and purposive; replication logic: theoretical or literal replication
Multiple sources of evidence	• Multiple sources of evidence for comprehensive depth and breadth of inquiry • Methods of data collection: interviews, observations, focus groups, artefact and document review, questionnaires and/or surveys • Methods of analysis: vary and depend on data collection methods and cases; need to be systematic and rigorous • Triangulation highly valued and commonly employed
Case study design	• Descriptive, exploratory, explanatory, illustrative, evaluative • Single or multiple cases • Embedded or holistic • Particularistic, heuristic, descriptive • Intrinsic, instrumental, and collective

The conceptual framework is applied to illustrate the expected insights gained by the thesis. It is used to formulate hypotheses that will be tested by solving the research objectives. For this purpose, the conceptual framework explains the major cause-effect relationships between the identified variables

(Swaen, 2015). Furthermore, the thesis applies semi-systematic review to solve RO 1. The purpose of this approach is to create an overview of the research area and is applied to rather broad research questions. It is focussed on research articles and review results that contribute, for instance, to the presentation of the state of knowledge in the research area (Snyder, 2019).

The particular methods for theorem proof (ontologies, first-order logics) and simulation (SD) will be discussed in more detail in Section 3.2.

3.1.4 Research Choice

As discussed in the previous sub-section, the thesis applies multiple methods to gather and analyse data and to solve the research objectives. These methods can be characterised as either qualitative (e.g., expert interviews as part of the case study) or quantitative (e.g., simulation). According to Roch (2017), this type of selection describes a mixed-method approach and enables a researcher to examine the topic under study from various perspectives. As applied in this thesis, the mixed-method approach can be derived from the particular research objectives. To apply quantitative techniques, the collected information must consist of any type of numeric data or must be transferable into a numeric form. Therefore, the preparation prior to the data collection must consider these criteria by considering in the questionnaire that interviews must supply numeric values in addition to qualitative answers. The qualitative techniques require information in written statements that can be interpreted by the researcher. Sources for this type of information include expert interviews or existing literature and documentation. Yin (2009) pointed out that mixed-methods may improve research in complex environments on a broader level than one research method allows.

3.1.5 Time Horizon

The time horizon of this research project is cross-sectional, because it presents a snapshot view of a particular situation at a specific point in time. Furthermore, it confines the duration of data collection and research to a short period of time (Saunders et al., 2009). The case study is performed within a limited timeframe and observes the behaviours of a SI PS that are present during this timeframe based on expert interviews and company-internal documentations. Consequently, the newly developed models in this thesis are valid for the present day impacts of PA on SI PS performance.

3.1.6 Techniques for Data Collection and Analysis

At a manufacturing facility of the case study partner, a real SI PS will be analysed. Different methods per PS aspect are used for data collection. The project uses semi-structured interviews (SSI) to collect primary data and Business Process Model and Notation (BPMN) to present secondary data based on internal documentation from the case study company.

The application of SSI provides the flexibility to experience the independent thoughts of each individual in a group (Adams, 2015). It enables the researcher to gain deeper insights into an expert's knowledge compared to a structured interview. Despite this flexibility, it supports the comparability of answers between interviewees better than unstructured interviews. The design of the questions are discussed in Chapter 5. BPMN is an industry standard that allows the illustration of business process models that can be understood by both process users and analysts. BPMN models describe a timely and logically dependent flow of events, decisions and activities (Schlauderer and Overhage, 2017).

The qualitative part of the raw primary data is analysed through thematic coding. This technique breaks up data into parts of the same kind. Coding finds themes in text by analysing the meaning of words and sentence structure. A researcher identifies themes that are most frequent in interview results to understand the importance to the object under study (Medelyan, 2019). Coding involves description of raw data, categorisation of descriptive codes and development into analytic codes (Gibbs, 2010). Thematic coding has been applied to secondary data that has been collected through the literature review, as well as to the primary data from the expert interviews. Roch (2017) suggested performing basic quantitative analyses of the primary data independent of the actual research objectives. Typical techniques are descriptive statistics and visualisation in charts to gain insights, such as frequencies of terms or the mean and standard deviation of a variable. These results provide a first overview of the collected data and prevents the researcher from failures due to unsound interpretations of results in the later research process.

3.2 Specific Research Methods

3.2.1 Ontology

Ontology is a method to model the structure of a system, which includes, for instance, essential entities and their mutual relations. Some characteristics are similar to the concept of models that are designed upfront to implement databases or software. However, Haidegger et al. (2013) discussed some significant differences that are compared in Table 3-4. Ontologies are used in computer sciences since the end of 1980s to represent knowledge in an explicit and formal way. At that time, the main focus was on high reusability of knowledge during the system design phase and not on direct user or external system interaction (Dengel, 2012).

Table 3-4: Comparison of Models and Ontologies adapted from Haidegger et al. (2013, p. 1218)

Feature	Model	Ontology
Deployment	No need to be shared openly or only shared within a small group of developers.	Shared by all people in a domain or across many domains.
Open/Closed	Closed world (can be descriptive or prescriptive)	Open world assumption leads to descriptive models only.
Transformable	Can be transformed from one to another. Meta-models can be bridged between them.	Can only be mapped from one to another by using additional axioms. They need to be aligned to create a shared ontology.
Propagation of constraints	Can be propagated in both ways.	One way only.
Implementation level	At lower abstraction levels.	At computation-independent model levels.
Possibility of integration	Can be done via transformation and generation.	More difficult and done via lifting and bridging.
Abstraction level	More concrete. Models result in actual implementation.	More descriptive and abstract. Ontologies can be used for Knowledge representation and reasoning.

An ontology consists of a generalization or specialization hierarchy of concepts (also called classes or entities), which can be implemented as a taxonomy (Staab and Studer, 2009). Relations between concepts can also be inherited. Taxonomies are methods for classifying entities by their characteristics, and can refer to both the process and the end result (Bailey, 1994). The difference with normal taxonomies (e.g., dinosaur classifications) is that ontology classifications are not limited to a single hierarchy. Furthermore, they always specify the meaning of an association between two entities. In this way, it is possible to classify an entity by multiple aspects in parallel.

Nowadays, ontologies are an important method and widely used in the areas of knowledge sharing, artificial intelligence, robotics or autonomous systems in general. The Institute of Electrical and Electronics Engineers (IEEE) recommends ontologies as a major knowledge base for autonomous robots for the following reasons (Haidegger et al., 2013):

- Development and deployment of robots require standardization in terms of safety, liability and quality.
- Ontologies allow the description of the robot’s world, tasks and services precisely and unambiguously.
- Ontologies using formal standards such as Web Ontology Language (OWL) and can be easily shared between systems.
- The knowledge is not limited to the technical system, but extendible also to the human world around.

Ontology as a method will be applied to develop the core of the PPES. This core is extended by first-order logical rules that are discussed in the following sub-section.

3.2.2 First-Order Logic

The First-Order Logic (FOL) is a method related to model theory. It allows the unambiguous definition and interpretation of statements (so called axioms) and the generation of inferences based on those axioms. For this purpose, it uses a formal language. A formal language can be defined without any reference to an interpretation since it is based on well-formed formulas (Hunter, 1996, cop. 1971). The FOL can be seen as next step in the evolution of the propositional calculus. The propositional calculus is the formal basis of logic dealing with the notation and usage of logical symbols. Further, it is also employed with the definition of axioms and rules of inference as part of the discipline proof theory (Weisstein and Sakharov, n.d.).

FOL is using following basic expressions (Dangelmaier, 2017):

1) All symbols from the propositional calculus:
    a. logical negation: $\neg$
    b. logical implication: $\rightarrow$
    c. logical equivalence: $\leftrightarrow$
    d. logical conjunction ("and"): $\wedge$
    e. logical disjunction ("or"): $\vee$
2) Logical symbols to quantify an expression:
    a. universal quantifier: $\forall$
    b. existential quantifier: $\exists$
3) Variables that represent individuals as model participants generically.
4) Constants that represent, for instance, a specific individual.
5) First-order predicates which act as classifiers on or relations between individuals.
6) Higher-order predicates that denote the attributes of attributes or relations or relations between attributes and relations. In fact, they are not part of the FOL but of the higher-order logic, which is not separated strictly from FOL in some German literature.

Single FOL expressions can be combined using the logical symbols to create new axioms. An example on the production environment demonstrates this approach with initially independent expressions:

a: "Production machines are located within the factory building."

b: "The factory building roof is water-resistant."

c: “It rains.”

d: “Production machines get wet.”

A major aspect of propositional calculus is the declaration of whether an expression is true or false. Depending on the truth-value of expressions, there exists several rules for logical connectives to build compound expressions. Usually, the rules can be visualized at one glance within a truth table, for instance, to characterize the logical implication between two expressions as shown in Table 3-5. A noteworthy rule is indicated by the second row: it is impossible to infer an expression, which is wrong, based on a true statement.

Table 3-5: Example of a Logical Implication

a	***b***	***a → b***
TRUE	*TRUE*	*TRUE*
TRUE	*FALSE*	*FALSE*
FALSE	*TRUE*	*TRUE*
FALSE	*FALSE*	*TRUE*

Looking at the previously stated expressions, the following statement could be created: “As long as the machines are within the factory building <u>and</u> the roof is water-resistant, they will not get wet while it is raining“. Equation (3.1) shows the propositional calculus for this statement.

$$a \wedge b \wedge c \rightarrow \neg d \tag{3.1}$$

Though the derived expression is negated, its truth-value is ‘true’ since expression d is false. Thus, the compound expression is true.

Propositional calculus is limited when the expression complexity is growing. More differentiated expressions require the consideration of objects and individuals as well as properties and mutual relationships (Avigad et al., 2017). Looking at the previous example, there could be scenarios that require more differentiation. Examples can be:

a) There are sub-parts of the factory, where the roof is not water-resistant.
b) There are machines that do not require such a protection.
c) There are other water-protections within the factory except the roof.

Equation (3.2) applies FOL using predicates and the existential quantifier to state that machines exist that do not require water-protection.

$$\exists m[Machines(m) \land \neg RequireWaterProtection(m)] \tag{3.2}$$

In this formula, m is a variable that represents individual objects. The formula indicates indirectly that there are also machines, which do require water-protection or other objects, which are no machines (e.g., transportation vehicles) that do not require water-protection.

In addition, the relationship between machines and factory can be expressed in more detail in terms of water-protection. Equation (3.3) shows this expression.

$$\exists m\big[isPartOf(m, Factory) \land \neg\big(RequireWaterProtection(m)\big)\big] \tag{3.3}$$

The formula says that objects exist that are part of the factory, but do not require water-protection. *Factory* is a constant which represents the single building and the predicate *isPartof* specifies the relation between any object and a particular Factory. In addition, the existential quantifier says that there are such objects, but there may also be others with different requirements.

A strength of FOL is the precise formulation of inference rules. Equation (3.4) demonstrates this capability and says that if an object m is part of another object a and a is part of *Factory*, then must m also be part of *Factory*.

$$\forall a\ \forall m[isPartOf(a, Factory) \land isPartOf(m, a) \longrightarrow isPartOf(m, Factory)] \tag{3.4}$$

The results of this thesis shall be shared with the research community. Hence, a global standard has been used to produce and store the rules, understandable by multiple persons, executable by multiple software tools, easy to exchange and capable of being extended. The literature research has led to the conclusion that the previously discussed OWL standard combined with a rule language based on FOL fulfils all of these requirements. With this approach, some of the logic expressions are modelled as part of the core ontology and others as explicit FOL rules.

For this purpose, the Semantic Web Rule Language (SWRL) has been applied, which is a common standard for rule-based development in combination with the ontology language OWL. The successful combination of these techniques has been proved by previous research projects in different environments, for instance:

- To model the management behaviour and information of IT network architectures in a semantic way (Guerrero et al., 2005)
- To imply the soil productivity grade (Ma et al., 2012).
- To model the knowledge about supply chain scenarios (Matheus et al., 2005).

SWRL was initially proposed to the World Wide Web Consortium (W3C) in 2004 as a combination of OWL and the Rule Markup Language. It includes high-level abstract syntax for Horn-like rules, an important type of FOL formula, and is also XML-based as is OWL (Horrocks et al., 2004). From a feature perspective, SWRL is a subset of FOL. For instance, negations and disjunctions cannot be written explicitly in expressions. However, these types of expressions can be modelled via OWL and, therefore, the full spectrum of FOL can be applied in combination with OWL and SWRL.

The following example demonstrates the implementation of ontology-based rules. Individuals (people) are classified into male or female. In addition, a connection between individuals states a parent-child relationship. From the FOL perspective, *male*, *female* and *isParent* are predicates. Figure 3-3 shows the graphical representation of this ontology.

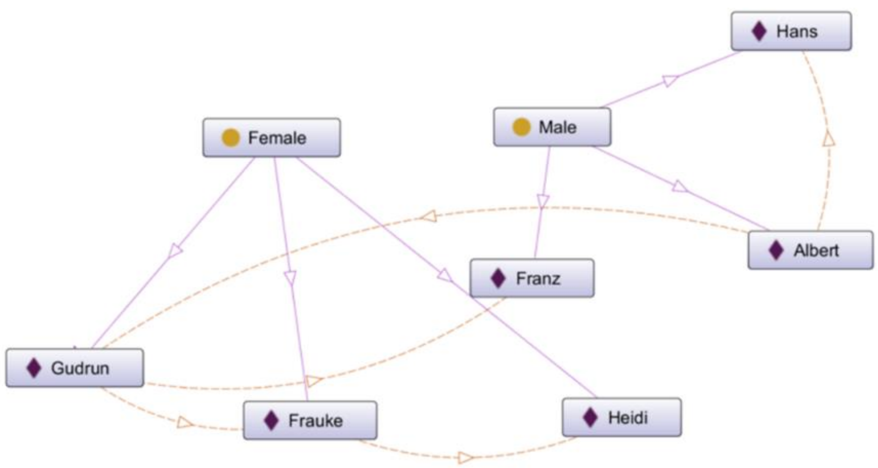


Figure 3-3: Example Ontology on People

In a separate section, additional rules are created to derive advanced information about the family relations:

R1: isParent(?x, ?y) ^ isParent(?x, ?z) ^ differentFrom(?y, ?z) -> hasSibling(?y, ?z)

R2: Male(?y) ^ hasSibling(?y, ?x) -> isBrother(?y, ?x)

R3: Female(?y) ^ hasSibling(?y, ?x) -> isSister(?y, ?x)

R4: isParent(?x, ?y) ^ isBrother(?z, ?x) -> isUncle(?z, ?y)

The rules describe formally when individuals are siblings (R1), what exactly makes a brother different from a sister (R2+R3) and when an individual is an uncle (R4). This type of description is a major difference to imperative programming languages like Java or C#, where only the calculation is defined, but not the meaning of the calculation. This gap prevents the calculations from being reused for similar use cases within a software, which were not considered by the programmers. With declarative programming languages like SWLR, the semantic of the calculation is understandable by the rule engine and further inferences can be created automatically. Once the rule engine is executed, new relationships are added to the ontology as visualized in Figure 3-4.

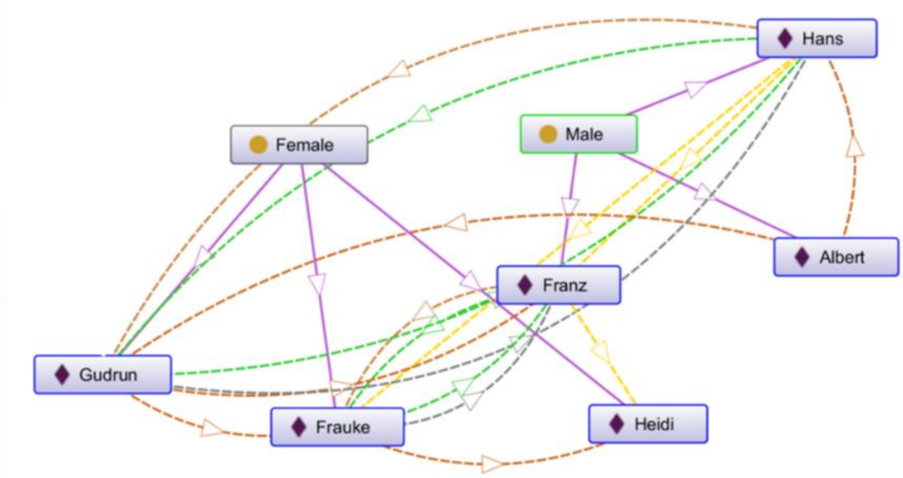


Figure 3-4: Example Ontology extended by Family Relations

The rule engine may create inferred axioms based on the ontology structure and characteristics. This is a powerful function either to generate new knowledge or – in case of wrong inferences – to confirm the ontology logics.

3.2.3 System Dynamics

According to Sterman (2000), SD is

> a method to enhance learning in complex systems. Just as an airline uses flight simulators to help pilots learn, system dynamics is, partly, a method for developing management flight simulators, often computer simulation models, to help us learn about dynamic complexity, understand the sources of policy resistance, and design more effective policies (p. 4).

Grösser (2018) defined SD as a methodology that is capable of modelling, simulating, analysing and designing dynamic-complex facts in socioeconomic systems. It was developed by Jaw W. Forrester in the 1950s to support managers within complex development of their enterprises and to improve the decision-making process. In economic studies, SD is also known as 'Business Dynamics' or 'Strategy Dynamics'.

Figure 3-5 presents a modelling process that is based on the proposal of Sterman (2000) to develop and apply a SD model. A modeller starts with articulating the problem under study, e.g., by defining why describing the problem and defining the key variables that must be considered for this problem. Once the problem is defined, a dynamic hypothesis can be formulated. This step explores the causal relationships of the key variables and maps them into a CLM.

Once the CLM is defined, the actual simulation model can be developed. This step includes the design of model structure and decision rules, the estimation of parameters and the general consistency tests. The final step applies the model to generate new insights into a system's behaviour. These insights allow the definition of new decision rules for the real system under study and the analysis of effects of these rules on the system.

According to Bossel (2004), the prediction ability of a SD model is principally not based on historically collected data, but on the clear definition of causes and effects. Therefore, system knowhow owners need to be interviewed to retrieve the structure and function of the system. The data demand for explanatory models is therefore:

- A set of data about causes and effects in the system structure.
- A set of characteristic parameters of single processes within the system.

However, Bossel emphasizes that though the data of time series is not required to create the model, the data is important for the succeeding model validation.

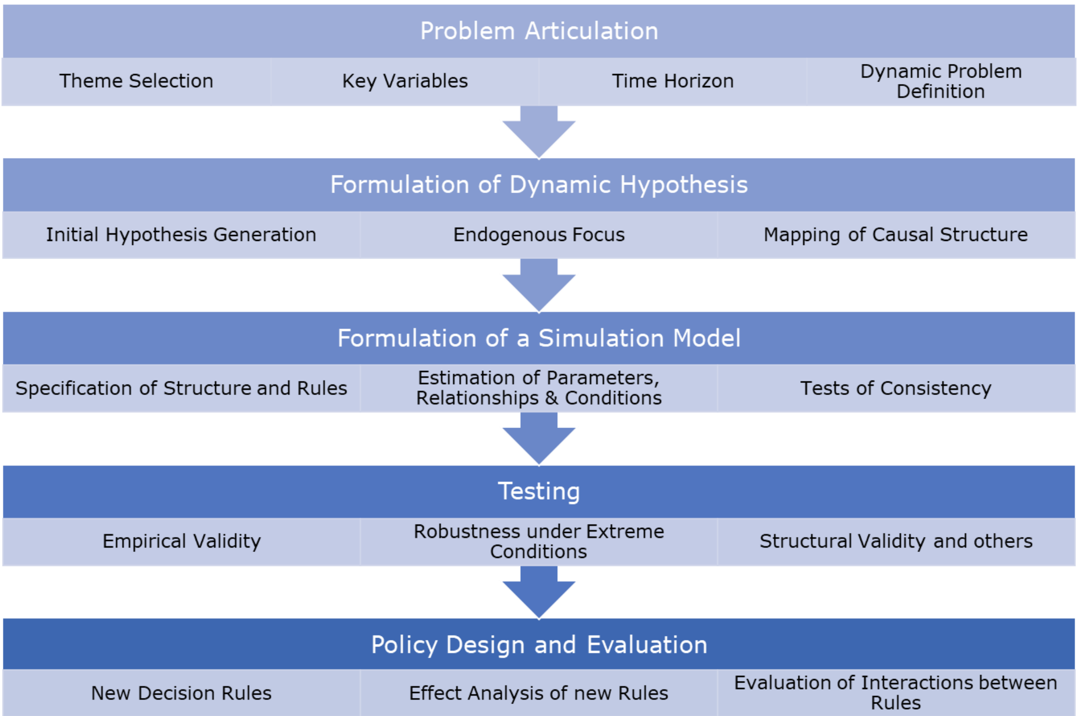


Figure 3-5: SD Modelling Process based on Sterman (2000)

Figure 3-6 shows a schematic of a CLM that consists of three nodes that influence each other. An arrow connects a source node to a target node, where the arrowhead points to the target node that is influenced by the source node. An influence can be positive or negative and is marked by the according sign ‘+’ or ‘–‘. A positive influence increases the value of the target node, whereas a negative decreases the value. For instance, the model states that if node 1 increases, it would increase node 2 and node 2 would, in turn, increase node 3. However, by increasing node 2, node 1 is decreased. To understand the overall system behaviour, these feedback loops must be considered. The effect of a feedback loop is marked by a feedback signal in the middle of an arrow circle as shown in Figure 3-6.

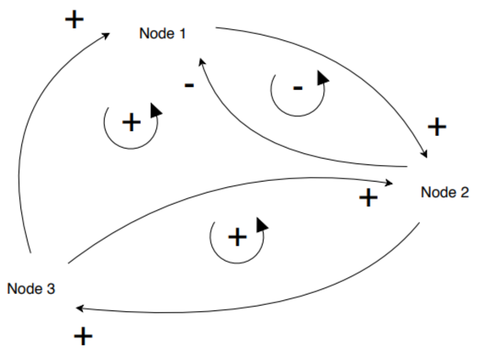


Figure 3-6: Example System Constellation with Feedback

A feedback signal only has the same sign as the initial arrow if the entire arrow circle consists of an even number of negative signs. Otherwise, with an odd number of negative signs, the feedback signal turns into the opposite. A negative feedback tends to stabilise the system whereas a positive feedback tends to lead to the destabilisation of the system (Bossel, 2004). This rule is also applied in Figure 3-6, where the feedback between node 1 and node 2 is negative, and therefore, a destabilisation of the system is expected.

According to Forrester (2013), the basic elements of SD models are stock variables (also known as level), flows and decision functions. Flows are elements that transport the required information between stocks and are controlled by decision functions. Stocks and flows have a clear mathematical dependency that is defined by the differential calculus. Equation (3.5) defines the flow v that is associated with a stock variable z over time. It means that v is the first derivative of z.

$$v = \frac{dz}{dt} \tag{3.5}$$

Due to this relationship, the value of z over a certain time span (from t_A to t_E) is defined as an integration shown in Equation (3.6).

$$z = \int_{t_A}^{t_E} v * dt \tag{3.6}$$

From a system model perspective, the flow v can be the difference between an additive flow and a subtracting flow as shown in Equation (3.7).

$$z = \int_{t_A}^{t_E} (v^{add} - v^{sub}) * dt \tag{3.7}$$

The system knowledge about causal relationships is expressed through the decision functions of the flows. If a feedback loop exists, v is dependent on the value of z. Forrester (2013) highlights, that system elements in reality are usually not dependent on the most recent value a stock, because a change cannot be applied infinitely fast. In any required case, this situation must be solved via an auxiliary variable as a transition layer. Stock-dependent flow functions can be formally written as shown in Equation (3.8). It represents an additive flow that applies the value of z from the previous period for both value calculation and case distinction.

$$v(t)^{add} = \begin{cases} (a+1) * z(t-1) * t, & z(t-1) < 50 \\ (a-1) * z(t-1) * t, & z(t-1) \geq 50 \end{cases} \tag{3.8}$$

Though the additive flow function is stock-dependent, the according subtractive flow function does not have to be as shown in Equation (3.9).

$$v(t)^{sub} = b * z(t-1) * t \tag{3.9}$$

The according SD diagram consists of stock z, flows v^{add} and v^{sub} and two parameters a and b and is visualised in Figure 3-7.

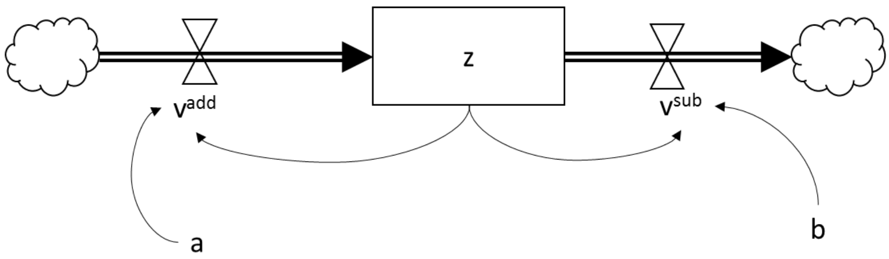


Figure 3-7: System Dynamic Model with two Feedbacks

Over the past few decades, SD has been applied to a large number of projects in various disciplines, for instance to examine the sustainable utilisation of water resources in China (Sun et al., 2017), challenges and opportunities in transportation (Shepherd, 2014), or to evaluate the investment risk of renewable energy (Liu and Zeng, 2017). SD is also applied to the area of manufacturing, for example:

- to analyse lean manufacturing strategies (Segura et al., 2019),
- to investigate the impact of additive manufacturing on the spare parts supply chain (Li et al., 2017),
- to design cost-effective Internet-of-Things solutions for production logistics (Qu et al., 2017),
- to support the decision-making process for the purchase of industrial robots (Elizondo-Noriega et al., 2019).

Admittedly, there are also limitations and drawbacks that have been discovered through the application of SD in several studies. These are based on the collection and classification of Sandrock (2006), and the noteworthy issues can be summarised as follows:

1. **General criticism**: SD does not consider established theories or approaches of system theory, and shows a limited system-theoretical foundation.
2. **Modelling process**: The process is less formalised; the validation is incomplete and misses a sensitivity analysis.
3. **Evaluation**: Value of simulation result is unclear because of issues in the modelling process.
4. **Technical aspects:** The execution of simulation runs requires long runtimes; models are functionally incomplete and some models are not sufficiently documented.

However, most of the critical articles are 30 to 50 years old. At least for modelling process and evaluation, Sterman (2000) and Bossel (2004) present comprehensive methods that overcome the mentioned issues.

3.3 Software Tools for the Research Project

3.3.1 Microsoft Excel

Microsoft Excel is a software program for organising, formatting and calculating data with formulas using a spreadsheet system. It is part of the Microsoft Office suite and produced by software company Microsoft. Further capabilities are the creation of several types of graphs, pivot tables and selfprogrammed macros using an integrated Visual Basic editor (Techopedia, 2019). The tool is applied to this project for several purposes such as consolidating the raw interview data, preparing SWRL rules, and comparing PdMSM results from different simulation runs.

Rationale for selection: Excel is an established and powerful calculation tool, which is also used at the case study company. All other selected tools in this research support Excel formats for importing or exporting data.

3.3.2 Cytoscape

Cytoscape is an open source software application that allows users to visualise molecular interaction networks and biological pathways. These networks can be integrated with annotations, gene expression profiles and other state data. Initially developed for biological research, Cytoscape became a general platform for complex network analysis and visualisation. Several plugins allow the configuration of network layouts (Cytoscape, 2018). This software is used to generate and visualize the CLM, which is one of the research objectives of this project.

Rationale for selection: The major advantage against ordinary graphic tools such as Microsoft Visio or draw.io is that the generated CLM is interactive and can also be exported as interactive web application. Hence, the CLM can be applied independently from the other created tools in this thesis, which underpins its relevance as single research objective.

3.3.3 Protégé

Protégé is an open source ontology editor and framework for building knowledge-based systems in several areas such as biomedicine, e-commerce and organisational modelling. The tool was originally developed at Stanford University.. It is based on java and provides a plug-and-play environment, which allows rapid prototyping and application development (Stanford University, n.d.). Protégé is applied in this project to develop and evaluate the PPES.

Rationale for selection: Protégé was found to be one of the most established ontology editors with particular strengths in building knowledge-based systems. In addition, an active community that consists of developers and users write documentations, contribute plug-ins and answer questions. Protégé fully supports OWL 2 and RDF specifications from the world wide web consortium, which fosters the reusability of PPES in further research projects.

3.3.4 PyCharm

PyCharm is a software produced by software company Jetbrains, which provides a professional edition as well as an open source community edition. For the scope of Python programming, the tool supports developer, for instance, by code completion, code inspection and code refactoring. It can be integrated with several scientific tools such as NumPy, IPython Notebook and matplotlib (Jetbrains, n.d.). The use of PyCharm in this research is to compare clustering-based term classifications against manually created classifications.

Rationale for selection: PyCharm is one of the most established integrated development environments for Python and even used at large companies such as Twitter and HP (Mindfire Solutions, 2018). Python itself counts to the most used programming languages and surpasses other languages especially in the area of machine-learning, e.g. R and Java (Developer Economics, 2017).

3.3.5 AnyLogic

AnyLogic is a simulation tool that is produced by a company of the same name. The company provides a professional edition for enterprises and a free edition for personal use. The tool consists of a graphical user interface for modelling complex environments in areas such as manufacturing, supply chain and healthcare. AnyLogic provides a so-called multi-method modelling approach, where different simulation techniques can be integrated seamlessly. AnyLogic provides agent-based, discrete event and SD simulation models (AnyLogic, n.d.-b). AnyLogic is used in this project to develop PdMSM and to perform experiments in order to discover and quantify the dynamic impacts of PA on SI PS performance.

Rationale for selection: During the case study, it was found that AnyLogic is used for simulation purposes at the case study company. Hence, it was concluded that the PdMSM could be efficiently applied, because the software and modelling knowledge are present and there are no further licensing costs. In addition, due to the multi-method approach, other existing models could be potentially integrated with the PdMSM.

3.4 Research Design

Based on the previously discussed sections, the design of the research project can be developed that composes research methodology and methods in order to resolve the research objectives of this thesis. Figure 3-8 presents the research design for this thesis.

The research design presents a comprehensive overview of which methods are used in which order to achieve which specific research objective. The method sequence is organised as proposed by the deductive approach and supports the SD modelling process. The research project starts with the literature review that provides specific insights into SI industry and value chains as well as PA methods and applications in SI. These results are used to develop a conceptual framework, which underpins the formulation of the research objectives for this thesis.

Through the semi-systematic review of research articles, existing performance models in SI manufacturing are examined to understand their goals and techniques and to verify whether any existing model is suitable for this research project. These results solve RO 1.

The next phase in the project is the case study that is performed at a real SI company. Primary data is collected through semi-structured interviews and secondary data from company-internal documents. After basic data analysis and evaluation, a CLM is developed that presents the direct influences between PS elements and PA characteristics. This model solves RO 2 and is the basis for the verification phase of the project.

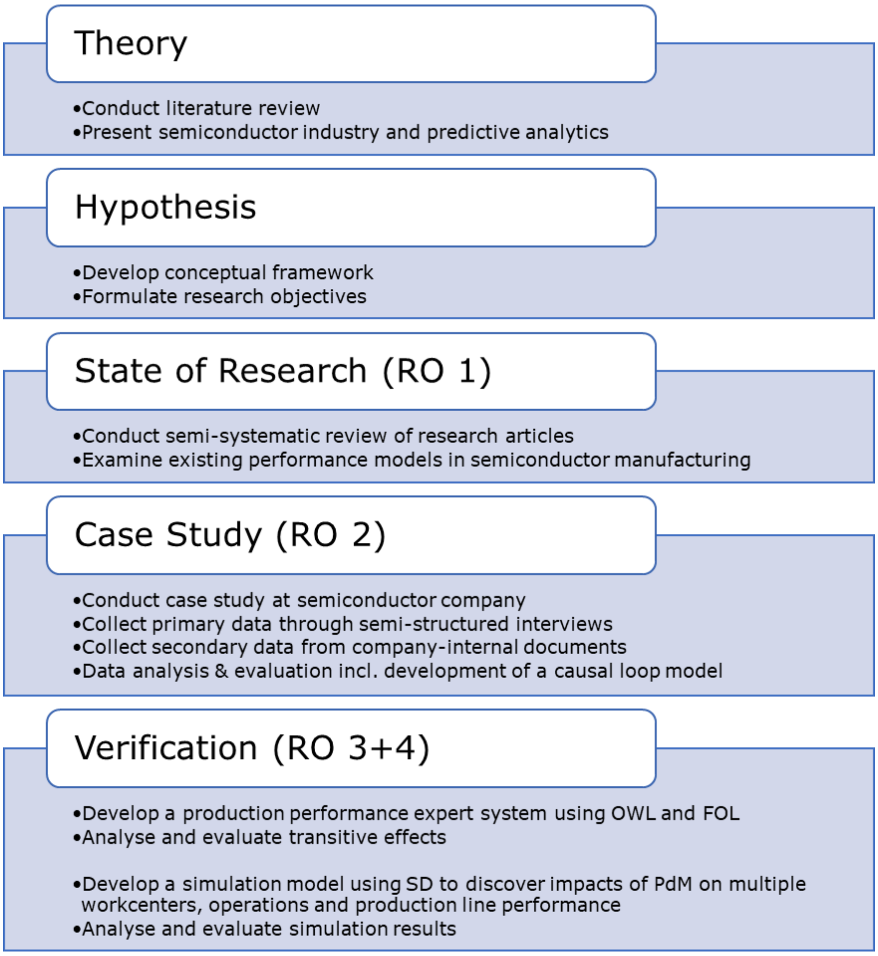


Figure 3-8: Research Design

After developing a PPES by application of ontology and first-order logic, the transitive effects of PA on PS performance can be analysed and evaluated qualitatively. These results solve RO 3. Finally, a SD-based simulation model has been developed to examine workcenter- and operation-specific impacts of PA on the overall PS performance. These quantitative results are analysed and evaluated to gain new knowledge about differentiated benefits and limitations of PA in semiconductor manufacturing. By completing this activity, RO 4 is solved.

3.5 Ethical issues

According to Strandberg (2019) poor research ethics could lead to the distrust of research results, lost funding and retraction of publications. The study summarises major ethical principles from previous and related research that must be addressed. Table 3-6 lists these principles and summaries.

Table 3-6: Important Ethical Principles (Strandberg, 2019, p. 2)

Ethical Principle	Summary
Consent	Participation should be voluntary and withdrawal possible at any time. Participants should be informed of this in a way that they can understand.
Beneficence	The welfare of participants and the greater good for society should be considered.
Confidentiality	The privacy and confidentiality of the participants must be protected in order to minimize the impact of the study on their integrity.
Scientific value	Research should yield fruitful results for the good of society and not be random or unnecessary.
Researcher skill	The researcher should have adequate skills.
Justice	It is unjust to let one group carry the burden of research while another benefits from the research.
Respect for law	Relevant laws should be obeyed.
Ethical reviews	An independent ethics board should comment on, guide and approve studies involving humans.

It has been ensured that each of these principles has been applied to this thesis.

Singer and Vinson (1999) pointed out that traditional ethical standards cannot immediately be applied in research that is conducted in industrial environments. This is because, in addition to the researcher, industrial representatives need to ensure that ethical codes are applied in order to protect themselves from litigation. For this purpose, the researcher must inform the representatives about the research content. This information consists of at least how the researcher plans to use the data, how the data will be stored and who will have access to it. To address these issues, this research project was presented to the workers' council at the case study company prior to the start of the study. The workers' council together with the researcher agreed on the standards and boundaries that had to be considered for data acquisition that would affect employees. In addition, the researcher presented the research content to the responsible department managers who were to evaluate the criticality of the data and use.

Chapter 4 Predicting and Evaluating Production System Performance in SI

4.1 Introduction

In the context of this thesis, performance models (PMs) are a technique that is capable of predicting and evaluating the future execution of a manufacturing process under varying circumstances. PMs can be applied to simulation studies to forecast the values of key performance indicators (KPIs). The predicted development of KPI values enables a company to understand causes and effects within the PS and to make appropriate decisions in order to achieve predicted improvements in reality.

In this chapter, the definition and components of a PS are firstly presented. Then, an appropriate way of evaluating PS performance is narrowed down for this thesis. The following section discusses the SI PS performance indicators and metrics that are relevant to this thesis. Finally, PMs in the SI are presented and discussed.

4.2 Production System

The PS is a core component of any company that produces physical products. The literature describes different ways to define a PS depending on the context and goal. According to Porter's model, a PS is part of the primary activities along the value chain. Other primary activities are inbound and outbound logistics, marketing and sales, as well as after sales service. These activities are separated from so-called support activities such as human resource management and firm infrastructure, which do not have a direct impact on the creation or logistics of material and products (Barnes, 2001). As discussed in Chapter 2, this model is not seen as suitable to SI PS. In the 1950s, Ishikawa invented the widely known manufacturing fishbone diagram that consists of the 4M method to evaluate the factors that affect the waste, as shown in Figure 4-1. Each *M* stands for a participant of the PS that is, from a lean perspective, also a candidate for waste (Chiarini, 2013).

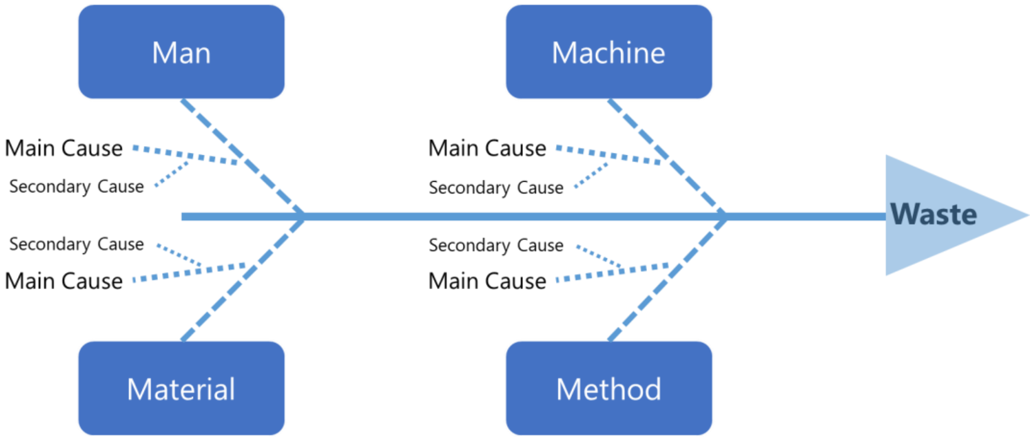


Figure 4-1: Ishikawa Manufacturing Fishbone Diagram (own visualization)

The main idea of this method is to reduce as much as possible the waste factors of each participant of the PS. These factors must be identified during a cause-and-effect analysis. The fishbone diagram supports classifying causes and effects per participant at a company and reveals dependencies between main causes and secondary causes. Generally, the Toyota Production System highlighted seven general kinds of waste, called *Muda*. These are transportation, inventory, motion, waiting, over-production, over-engineering and defects (Refa, 2019). In the semiconductor industry, there are waste factors such as handling and clothing for the category 'man', size and electrical properties for the category 'material', humidity and temperature for the category 'machine' and testing and protective structures for the category 'method' (Sood, 2013). Each of these participants plays a specific role during production. Therefore, waste analysis and optimisation require comprehensive knowledge about the core business processes that are related to production. To access this knowledge, experts from different disciplines, such as process engineering, production planning and operations, have to participate in workshops and work together.

The supply chain operations reference (SCOR) model provides a standardised way to collect and define such processes on three levels. This is not limited to the flow of a process, but includes also the participants, the recommended skills and common ways for measuring the process performance. On the first level, the SCOR model consists of five general management processes: plan, source, make, deliver and return. The PS processes are part of the *make* management process, and thus, they form the second level. The SCOR model principally allows the definition of interactions between single processes, which prevents process designers from building redundant flow designs. On the third level, the detailed flows, participants, inputs, outputs, performance metrics and even best practices are defined (Stephens, 2001).

A further view of a PS, especially in this project's context, refers to a closed-loop system that allows the analysis of causes and effects during a material transformation. Figure 4-2 shows this approach (Kaufmann and Hülsebusch, 2015).

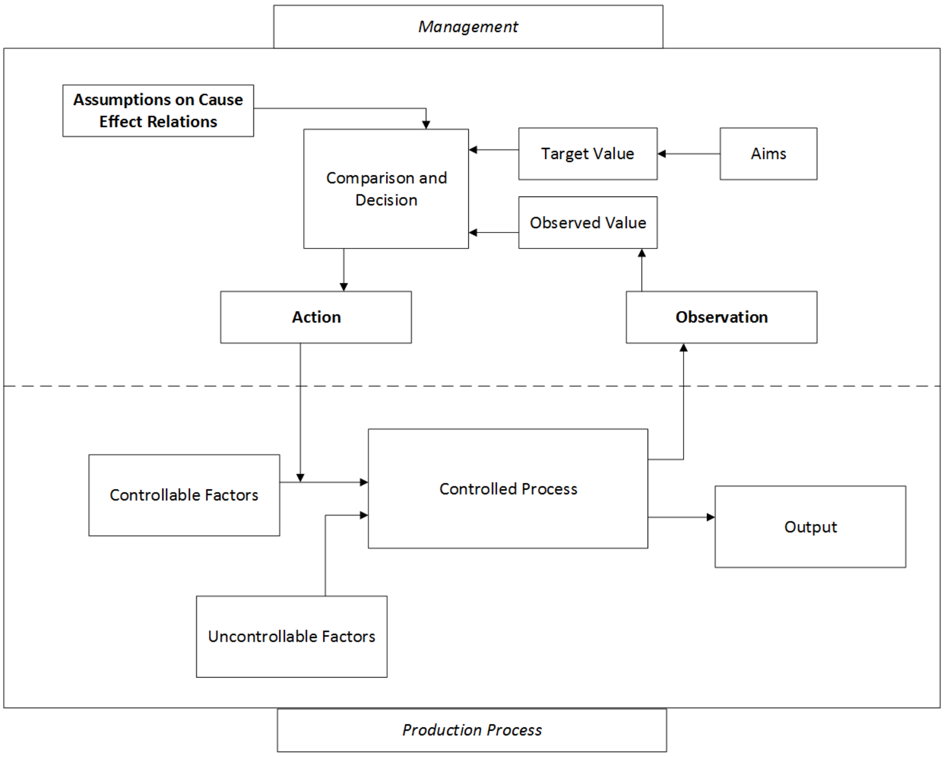


Figure 4-2: Cybernetic Model of a Production System inspired by Kaufmann and Hülsebusch (2015)

Such a model depicts interdependencies between PS elements and their characteristics. Whereas the 4M method points to single participants and the Value Chain and SCOR model concentrate on single processes, this way of modelling seeks causal relationships between participants and processes to control their execution continuously. These relationships enable a different interpretation of measured KPIs since they also include unexpected side effects from other processes. Kaufmann and Hülsebusch (2015) considered a production process to be controlled if the impact factors have been analysed and classified as controllable or uncontrollable. In this context, uncontrollable factors are effects from outside the PS, which cannot be changed actively, such as weather conditions and economic trends. Furthermore, possible actions that can change the controlled factors must be categorised. Values from an automated generation of data can be observed regularly and compared against target values. A knowledge base that consists of assumptions on cause-and-effect relations supports managers during the comparison and decision-making process. Depending on the results, the decisions may lead to a control action that directly affects controllable factors. In a simple way, this cybernetic approach is similar to a thermostat as a component of an ordinary heater.

This thesis focuses on qualitative as well as quantitative effects based on causal relationships, and thus, a PS is treated similarly in this thesis to the definition of Kaufmann and Hülsebusch (2015). In addition, it involves knowledge from the other described models if applicable. In this sense, a PS can be formally defined as the sextuple in Equation (4.1).

$$PS = \langle BP, P, R, I, O, T \rangle \tag{4.1}$$

Where:

BP:	The core business processes that directly affect the material transformation.
P:	All factory objects that can be classified as one of the four partners. They are primarily involved in creating a product.
R:	The relations between partners of the PS. They are used for the cause-and-effect knowledge base.
I:	All controllable input factors for partners to execute.
O:	All measurable output from a transformation process.
T:	Target values for performance indicators.

Possibly, PS PMs consider only parts from Equation (4.1) based on selected targets. For instance, projects for quality assurance seek for different insights than cost optimization projects. Hence, a PM does not need to depict the full PS in every case.

4.3 Evaluation of PS Performance

In order to manage and improve the performance of a SI PS in a targeted manner, a company must be clear about what ‘performance’ actually means and which performance characteristics are important to them. Though this assertion sounds trivial, Iannone and Elena (2013) pointed out that terms in this context are often mixed-up. Therefore, they proposed a delimitation to evaluate a transformation process from different perspectives: (1) efficiency, which stands for the ratio between actual input and a reference input, (2) effectiveness, which refers to the ratio between actual output and a reference output, and (3) productivity, which means the ratio between actual input and actual output. In particular, the authors considered downtime losses, speed losses and quality losses to have negative effects on the effectiveness. However, this demarcation is not commonly shared in literature. Oechsner et al. (2002) discussed an overall fab effectiveness (OFE) as a measure to evaluate an entire wafer fabrication facility. This measure was derived from the previously established overall equipment effectiveness (OEE) that is only valid on machine-level. They considered metrics such as cycle time efficiency, percentage of rework, yield and capacity utilization. It is seen as noteworthy that the authors defined 'performance' very limited as an aspect of OEE as defined in Equation (4.2).

$$Performance_m = \frac{t_m^{productive}}{t_m^{up}} * \frac{n^{actual}}{n^{theoretical}} \tag{4.2}$$

Where: *m* refers to a particular machine, $t_m^{productive}$ is the productive time of a machine, t_m^{up} is the overall uptime of a machine, n^{actual} is the number of units that was actually produced, and $n^{theoretical}$ is the number of units that could be produced theoretically.

Nicholds et al. (2018) demarcated 'performance' from the 'overall system effectiveness' (OSE). According to the authors, OSE includes measures such as availability, utilization and production efficiency, whereas 'performance' was narrowed down to characteristics that influence the OSE, e.g. average line staff and maximum output capacity. In contrast, Toni and Tonchia (2001) used the term 'performance' to evaluate operations more generally and divided it into cost performance and non-cost performance that includes time, flexibility and quality. Cost performance can be measured, for instance, by machinery saturation and work-in-process level, whereas non-cost performance considers measures such as machine availability, process speed and reworks. This type of performance distinction is also supported by Neely et al. (1995), who proposed to evaluate PS performance from following perspectives: (1) time, (2) quality, (3) flexibility, and (4) costs. For SI PS, typical KPIs from these perspectives are cycle time (time), yield (quality), flexibility in product mix (flexibility), and product costs (costs).

The literature review indicates an inconsistent definition of the term ‘performance’ in the area of manufacturing. It is not commonly agreed in which way it is related to ‘efficiency’, ‘effectiveness’ and ‘productivity’. In addition, whereas Iannone and Elena (2013) delimitated ‘efficiency’ from ‘effectiveness’, Nicholds et al. (2018) considered ‘production efficiency’ as part of OSE as a measure of effectiveness. A similar issue was detected for the term OEE, that some authors called a measure for efficiency (e.g. Oechsner et al. (2002) and Azizi (2015)) and others considered as a measure of effectiveness (e.g. deRon and Rooda (2005) and Nicholds et al. (2018)).

Therefore, a clear definition must be established within this project. It is proposed to focus only on the term ‘performance’ and to narrow it down for the scope of this thesis. With regards to the conceptual framework that proposes challenges in SI value chains that are expected to be mastered by PA and PdM in particular, ‘performance’ will be evaluated from following non-cost perspectives:

1) Logistics
2) Quality
3) Engineering
4) Maintenance

These perspectives are a subset of the categories that comprise SI value chain challenges as proposed in Chapter 2. It is implied that the actual values of PS KPIs reflect the ability of a SI company to master particular challenges in SI value chains. For instance, the ability to overcome the challenge that high utilization is required due to cost-intensive equipment can be measured by the KPI ‘utilization’ that refers to a specific workcenter. If PA is capable of increasing this KPI, it is concluded that PA supports to overcome the underlying challenge. Hence, the following section presents the KPIs and metrics in SI that are most relevant to this project based on the four perspectives mentioned above.

4.4 Performance Indicators and Metrics in the SI

KPIs are customisable business metrics utilised to visualise statuses and trends in an organisation. They allow a company to measure progress toward these objectives. Key performance metrics usually consist of a target value and an actual value; the target value represents a quantitative goal that is important for a company to successfully run its business (Guzik, et al., 2004). Most KPIs in this thesis have been officially defined by or based on standards from the SEMI organisation (SEMI, 2017). Others are based on the common standards from Little's Law (Little and Graves, 2008) and Factory Physics (Hopp and Spearman, 2011). Due to this foundation, the results of the thesis are expected to be valid to other SI companies as well. Due to the focus of the research project, KPIs related to man, method and material are only marginally relevant to this thesis and will be excluded. Each KPI is presented in detail including the rules for calculation. The correct understanding of each KPI is important to this project, since these indicators will be part of the PPES and the PdMSM. Prior to the detailed discussion, Table 4-1 lists the selected KPIs, their units of measure and associated category of challenge.

Table 4-1: Overview of the relevant KPIs for this project

Indicator	Unit	Category
Equipment availability	Percentage	Engineering
Operational efficiency	Percentage	Engineering
Overall equipment Efficiency	Percentage	Engineering
Cycle time	Time	Logistics
Flow factor	Factor	Logistics
Going rate	Units/time	Logistics
Operating curve	Function	Logistics
PS availability	Percentage	Logistics
Rate efficiency	Percentage	Logistics
Utilisation	Percentage	Logistics
Variability / Alpha	Coefficient	Logistics
Mean time between failures and mean time to failure	Time	Maintenance
Mean time offline	Time	Maintenance
Mean time to repair	Time	Maintenance
Quality efficiency	Percentage	Quality
Yield	Percentage	Quality

This section presents the most relevant KPIs to evaluate SI PS performance as defined in Section 4.3.

4.4.1 Logistics-Oriented KPIs

PS Availability (A_{PS})

Based on the 4M method from Ishikawa, Hansch and Schober (2015) developed the four-partner model to quantify PS performance based on the availability *A* of each partner. They specified the 4M method in more detail to gain clear results: ‘man’ is the operator, ‘machine‘ is the production tool (abbreviated as *m* in the formulas), ‘material‘ is the work in process (WIP) and ‘method‘ is the process. In this context, *process* refers to a single process entity that is part of a production route and not to the entire production process. Each partner refers to a particular availability metric:

A_m, A_{WIP}, $A_{Operator}$, and $A_{Process}$.

Prior to the calculation of the A_{PS}, it needs to be identified whether the four partners are statistically independent. If this is the case, the formula is as follows in Equation (4.3) (Hansch and Schober, 2015).

$$A_{PS} = A_m * A_{WIP} * A_{Operator} * A_{Process} \tag{4.3}$$

If the downtimes of the four partners are synchronised, the formula is as follows in Equation (4.4) (Hansch and Schober, 2015).

$$A_{PS} = Min\{A_m; A_{WIP}; A_{Operator}; A_{Process}\} \tag{4.4}$$

According to this formula, a synchronised PS always leads to higher productive time, assuming realistic percentages. The productive hours per day can be calculated by Equation (4.5) (Hansch and Schober, 2015).

$$Productive\ Hours\ per\ Day = 24[hours] * A_{PS} \tag{4.5}$$

Cycle Time

Cycle time (*CT*) is measured as the average time from a job being released into a station or onto a line to the time it is created (Hopp and Spearman, 2011). There are two established ways to calculate the *CT*. The first is based on Little’s Law and was created by John D. Little from research in the field of queuing theory. Equation (4.6) relates the work in progress (*WIP*) to the going rate (*GR*).

$$CT = \frac{WIP}{GR} \tag{4.6}$$

With the second method of calculation, the meaning of *CT* is more clearly highlighted. The *CT* is a value that can be compared to a theoretical time that is the minimum time required to execute a certain process. This time is called raw process time (*RPT*) or, in some literature, raw cycle time. More specifically, the *RPT* is the shortest time required to fabricate a product and is thus the sum of all production timeframes t_e, as defined by Equation (4.7) (Hansch and Schober, 2015).

$$RPT = \sum t_e \tag{4.7}$$

Where: t_e is a particular production time

In practise, the *RPT* is captured using time-recording methods when a new single process is released for the very first time at a machine. As defined by Equation (4.8), the *CT* is then defined as the sum of production time t_e and wait time T_W (Hansch and Schober, 2015).

$$CT = \sum T_W + \sum t_e \tag{4.8}$$

Where: t_e is a particular production time and T_W is the according wait time

However, it can be complicated and time-consuming in practice to measure wait times and calculate the *CT* using the second method of calculation. This is mainly due to complex production lines with a mix of various products and product-specific process characteristics. In such scenarios, companies must analyse whether it is possible to identify an overall *CT* or whether they must go for a product-specific *CT* (Hansch and Schober, 2015).

Going Rate

GR is also known as throughput and is measured as the average output of a production process per unit time. A process can be a single process entity at a machine or even the overarching production process at one plant (Hopp and Spearman, 2011). The correct dimension depends on the actual measurement goal, such as sales forecast or optimizing single process steps. According to Hansch and Schober (2015), *GR* can be either measured or calculated based on Little’s Law, which is a transformation of Equation

(4.6). The generic formula to measure the throughput is defined by Equation (4.9).

$$GR = \frac{n^{actual}}{t} \tag{4.9}$$

Where: n^{actual} is the number of units that was actually produced and *t* refers to a specific period.

If the *GR* is used as a tool metric, it specifies a certain tool's speed. The daily going rate (*DGR*) can be calculated as an indicator for potential performance loss compared to the theoretical *GR* In combination with A_{PS}. It specifies the number of units that can be manufactured in one day under certain circumstances of availability. It must be noted that the *DGR* is also dependent on the synchronicity of the PS partners. Inspired by Hansch and Schober (2015), the formula can be shortened and defined by Equation (4.10).

$$DGR[units] = \frac{n^{actual}}{t} * A_{PS} * 24[hours] \tag{4.10}$$

Where: n^{actual} is the number of units that was actually produced, *t* refers to a specific period and A_{PS} is the PS availability

Flow Factor

The flow factor (*FF*) is a multiplier, which specifies how much the *CT* exceeds the *RPT*. Thus, it describes how much longer the fabrication time is compared to the theoretically best value. Since it is a rather generic metric, it can be used to compare the execution performance of different tools, production lines or plants independently from process details (Hansch and Schober, 2015). The formula is as follows in Equation (4.11).

$$FF = \frac{CT}{RPT} \tag{4.11}$$

Variability (Alpha / α)

Variability α is a statistical metric that specifies the stability of a process. It quantifies the deviation of serving times for production lots that arrived at a new operation (Hansch and Schober, 2015). There are several statistical metrics required for calculating α:

- The mean values μ_e and μ_a for serving time *e* and arrival time *a.*

- The standard deviations $\sigma_e$and σ_a.
- The coefficients of variation c_e and c_a.

The formula to calculate α is as follows in Equation (4.12).

$$\alpha = \frac{c_a^2 + c_e^2}{2} \tag{4.12}$$

Where: c_e is the coefficient of variation for serving time and c_a is the coefficient of variation for arrival time

In this context, variability is seen as related to logistics. The variability of production processes in terms of less determinable results of a single process is related to engineering challenges but is not in the scope of this thesis.

Utilisation

Utilisation (*U*) is a dynamic performance parameter which sets the *GR* in relation to the maximum throughput per production unit; this maximum throughput is called ‘capacity’ (Hansch and Schober, 2015). If a machine is processing fewer wafers per run than is theoretically possible, the machine’s capacity is not fully utilised. The reasons for this can be various. For instance, many wafers may have entered a limited timeframe where a single production process has to be executed within. There is a maximum timespan between a pre-process and a final process. If this timespan is exceeded, the wafers may be damaged due to chemical reactions. Thus, even if the machine capacity is higher than the number of wafers that is currently loaded, the process must be started even though the machine is not fully utilised.

First, the possible capacity must be determined. The literature lists two types of capacities: a) capacity of a single machine and b) capacity of an overarching production unit. Equation (4.13) defines the calculation for a single machine (Hansch and Schober, 2015).

$$Capa_{Tool} = 24[hours] * GR_{Tool} * A_{Process} * A_{Tool} \tag{4.13}$$

Equation (4.14) defines the calculation for an overarching production unit (Hansch and Schober, 2015).

$$Capa_{Prod\ Unit} = 24[hours] * GR_{Prod\ Unit} * A_{Process} * A_{Tool} * A_{Operator} \quad (4.14)$$

Even if the capacity can be calculated on a regular basis, the literature proposes taking the value as fixed since it acts as an input variable in PMs. With the capacity and the *GR*, utilisation can be calculated using Equation (4.15) (Hansch and Schober, 2015).

$$U = \frac{GR}{Capa} \quad (4.15)$$

Depending on the chosen dimensions of capacity and *GR*, the value of *U* must be correctly interpreted.

Operating Curve

The operating curve (OC) is an indicator to describe the performance of an entire production unit and was developed based on the results of queuing theory. Its calculation basis allows deeper study of PS behaviour under varying conditions. Thus, it is an important component of simulation models that are concerned with theoretical PS improvements (Weigert, 2013). The OC relates two KPIs, with one acting as a dependent (d) variable and the other acting as an independent (i) variable. Various associations are described in the literature on Little's Law (Hansch and Schober, 2015):

- GR (d) and WIP (i)
- CT (d) and GR (i)
- GR (d) and CT (i)
- WIP (d) and CT (i)
- WIP (d) and GR (i)
- CT (d) and WIP (i)
- FF (d) and U (i)

Depending on the associating variables, the OC can be calculated using a specific formula. For instance, Equation (4.16) shows the calculation of *CT* (d) based on *GR* (i), where *U* is calculated based on *GR* (Hansch and Schober, 2015).

$$CT = \alpha * \frac{U}{1-U} * RPT + RPT \quad (4.16)$$

A further example is the calculation of *FF* (d) based on *U* (i) as shown in Equation (4.17) (Hansch and Schober, 2015).

$$FF = \alpha * \frac{U}{1-U} + 1 \tag{4.17}$$

Due to the logics of equation, every point on one OC represents the same level of performance. To improve a factory's performance, the entire OC must be moved onto the x-axis (Weber and Fayed, 2010).

Rate efficiency

Rate efficiency (*RE*) defines the relation between the produced units n^{actual} and the theoretically produced units $n^{theoretical}$ that were realistic during the production time (Pomorski, 1997). It is defined by Equation (4.18).

$$RE = \frac{n^{actual}}{n^{theoretical}} \tag{4.18}$$

Where: n^{actual} is the number of units that was actually produced and and $n^{theoretical}$ is the number of units that could be produced theoretically.

4.4.2 Quality-Oriented KPIs

Yield

In general, yield is a percentage indicator that shows the relation between the units that fulfil the desired product specification and the units that do not meet this specification. Hilsenbeck (2005) pointed out that yield can decrease due to random defects during the fabrication (e.g. particles on the wafer that cause disconnections of a chip) or due to systematic issues (e.g. incorrect layers or poor chip design). Yield can be measured as 'line yield' Y_{line} and 'die yield' Y_{die}. These two measures have a different granularity and complement one another. 'Line yield' is on wafer level and refers to the percentage of wafers that successfully passed the manufacturing process (Hilsenbeck, 2005). It is defined by Equation (4.19)

$$Y_{line} = \frac{\sum_{p=1}^{P}\sum_{l=1}^{L_p} n_{lp}^{out}}{\sum_{p=1}^{P}\sum_{l=1}^{L_p} n_{lp}^{in}} \tag{4.19}$$

Where: *P* refers to the number of products, *L* refers to the number of lots that belong to a product, n_{lp}^{out} is the number of wafers that passed the manufacturing process and n_{lp}^{in} is the number of wafers that have entered the manufacturing process.

'Line yield' is typically measured prior to the wafer test, where every chip on a wafer is tested against the functional specification. Based on the result of these tests, the 'die yield' can be calculated using Equation (4.20) (Hilsenbeck, 2005).

$$Y_{line} = \frac{\sum_{p=1}^{P} \sum_{l=1}^{L_p} \frac{m_{lp}^{passed}}{m_p}}{\sum_{p=1}^{P} \sum_{l=1}^{L_p} n_{lp}^{tested}} \tag{4.20}$$

Where: *P* refers to the number of products, *L* refers to the number of lots that belong to a product, m_{lp}^{passed} is the number of chips on a particular wafer within a specific lot that belongs to a particular product that passed the test, m_p is the number of chips per wafer for a particular product, n_{lp}^{out} is the number of wafers that passed the manufacturing process and n_{lp}^{in} is the number of wafers that have entered the manufacturing process.

To calculate the overall yield Y that considers the total losses of wafers as well as the functional failures per chip, both measures need to be consolidated as defined by Equation (4.21) (Hilsenbeck, 2005).

$$Y = Y_{line} * Y_{die} \tag{4.21}$$

Quality efficiency

Quality efficiency (*QE*) defines the relation between the units approved by quality control, which excludes units to rework n^{rework} as well as units to scrap n^{scrap}, and all produced units n^{actual} (Pomorski, 1997). It is defined by Equation (4.22).

$$QE = \frac{n^{actual} - (n^{rework} + n^{scrap})}{n^{actual}} \tag{4.22}$$

Where: n^{actual} is the number of units that was actually produced, n^{rework} is the number of units that requires rework and n^{scrap} is the number of units that failed.

In contrast to yield, *QE* considers also the number of units that require rework. Therefore, it provides a different view from quality perspective.

4.4.3 Engineering-Oriented KPIs

Machine availability

According to Pomorski (1997), machine availability (*A_m*) defines the relation between a machine's uptime t_m^{up} and the total time t^{total} of a considered period as defined in Equation (4.23).

$$A_m = \frac{t_m^{up}}{t^{total}} \tag{4.23}$$

Where: t_m^{up} is the overall uptime of a machine and t^{total} is the total time.

Machine availability is also a part of the overall PS availability that was discussed in 4.4.1.

Operational efficiency

Operational efficiency (*OE*) defines the relation between a machine's overall uptime, which includes a machine's pure uptime t_m^{up} as well as its idle time t_m^{idle}, and the time used for production $t_m^{productive}$ (Pomorski, 1997). It is defined by Equation (4.24).

$$OE = \frac{t_m^{productive}}{t_m^{up} - t_m^{idle}} \tag{4.24}$$

Where: $t_m^{productive}$ is the productive time of a machine, t_m^{up} is the overall uptime of a machine and t_m^{idle} is the idle time of a machine.

Overall Equipment Efficiency or Effectiveness

Overall equipment efficiency or effectiveness (*OEE*) is the key metric of total productive manufacturing and represents the productivity of a machine. It is defined by SEMI E79 and compares the actual performance of a particular machine *m* to its performance capabilities under ideal manufacturing conditions. Overall equipment effectiveness considers not only the machine uptime but also surrounding factors such as quality efficiency and rate efficiency. It consists of three generic elements: availability, performance efficiency and rate of quality. Overall equipment effectiveness is calculated by multiplying single metrics, which each represent a certain aspect of productivity (Pomorski, 1997). *OEE* itself is seen as a KPI that is related to engineering, since observations at the case study company showed that engineering departments own the key responsibility over a machine and are the main audience for *OEE* reports. However, some of its sub-KPIs refer to challenges and perspectives that are related to logistics and quality. Therefore, these sub-KPIs are discussed within the according sub-sub-section. According to Pomorski (1997), *OEE* is calculated using Equation (4.25).

$$OEE = A_m * RE * OE * QE \tag{4.25}$$

Where: A_m is the machine availability, *RE* is the rate efficiency, *OE* is the operational efficiency and *QE* is the quality efficiency.

4.4.4 Maintenance-Oriented KPIs

Mean Time to Repair

The mean time to repair (*MTTR*) measures the maintainability of a machine. As defined in Equation (4.26), it represents the average time required to repair a failed machine component. It sets the overall time that was required for repair actions in relation to the overall number of failures over a certain amount of time (Hilsenbeck, 2005).

$$MTTR = \frac{1}{n} * \sum_{i=1}^{n} t_i^{repair} \tag{4.26}$$

Where: *n* is the number of failures and t_i^{repair} is the time required to repair a particular failure.

Mean Time to Failure and Mean Time Between Failures

Machine components can be repairable or not. If a component must be replaced completely (either due to a failure or planned lifecycle end), the meantime to failure (*MTTF*) is applied. If a component can be repaired after a failure, the meantime between failures (*MTBF*) is applied. Both KPIs are calculated using Equation (4.27) and represent the average time that passes between two failures (Olofsson, 2018).

$$MTTF/MTBF = \frac{\mathrm{t}^{productive}}{n} \tag{4.27}$$

Where: *n* is the number of failures and $\mathrm{t}^{productive}$ is the time where the machine was productive.

Mean Time Offline

To evaluate a machine's downtime history in combination with the number of issues, the meantime offline (*MTOL*) is applied. It calculates the relation between the overall downtime period and the number of interruptions within a certain timespan, as shown in Equation (4.28) (Hilsenbeck, 2005).

$$MTOL = \frac{1}{n} * \sum_{i=1}^{n} t_i^{down} \tag{4.28}$$

Where: n is the number of failures and t_i^{down} is the time where the machine was down per failure.

4.5 Performance Models with Focus on SI

In computer science, a PM is a model created to define the significant aspects of how a proposed or actual system operates in terms of resources consumed, contention for resources and delays from processing or physical limitations. Such models can be interpreted by a software tool to simulate the system's behaviour based on the information contained in the PM (Illingworth and Pyle, 2004). Through simulation runs, the model results can be tested against varying circumstances. Thus, a PM allows the prediction of future KPIs under changing conditions without the necessity of applying these changes to the real system. The main difference between performance measurement systems (PMSes) and PMs is, therefore, that PMSes serve to analyse actual performance values from the real system's processes, whereas PMs serve to forecast future performance values.

To find existing models from academic publications, several global literature databases were searched. To focus on current and relevant models and methods, the earliest publication date was set to the year 2005. The following are the reasons for this limitation of publication date:

1) The research context of PA is quite new, and the initial literature review showed that scientific results have been published mainly during the past several years.

2) If a PM from an older publication is important, it has probably become a standard in the SI. If it could solve the project's challenges, it would be revealed during the case study.
3) The study seeks to demonstrate that none of the current research projects employed with PM in the SI has presented a solution to the challenges from this study.

Since the pure database research also showed results that were not relevant, further criteria for manual analysis were required to identify relevant models for this study:

1) A publication must present a PM according to the specification above (e.g., no frameworks, online control systems or fixed algorithms).
2) A model must cover the entire PS, not only one of the four partners (e.g., not only OEE for production machines).
3) A model must be concerned primarily with simulating PS KPI values as discussed in section 4.3 (e.g., no pollutant emission or delivery dates).
4) A model must focus on the overarching production process (e.g., not the introduction of new products, single sub-processes or IT system performance).

Under these criteria, the literature study identified 18 models from 183 relevant publications. Table 4-2 lists the titles and references of the relevant publications as well as the evaluated type of model that will be discussed in the following paragraphs.

In the next step, these models were analysed and classified according to the following categories: calculation type, core method for simulation and simulation goal. Furthermore, the models were examined against environment scalability, their ability to extend input parameters and output variables and their applicability to the evaluation of PA applications.

Table 4-2: List of Publications about Relevant Models

#	Title of Publication	Reference of Publication	Type of Model
1	"A Performance Analytical Model of Automated Material Handling System for Semiconductor Wafer Fabrication System"	(Zhang et al., 2015)	Analytical
2	"The Construction of Production Performance Prediction System for Semiconductor Manufacturing with Artificial Neural Networks "	(Huang, 1999)	MLB
3	"An Economic Manufacturing Quantity Model for a Two-Stage Assembly System with Imperfect Processes and Variable Production Rate"	(Chang et al., 2012)	Deterministic
4	"Impact of Production Control and System Factors in Semiconductor Wafer Fabrication"	(Qi et al., 2008)	Deterministic
5	"The Influence of Lot Size on Production Performance in Wafer Fabrication Based on Simulation"	(Tu and Lu, 2017)	Other
6	"Scheduling Policies in Multi-Product Manufacturing Systems with Sequence-Dependent Setup Times"	(Feng et al., 2011)	Statistical
7	"Mathematical Programming Approach to Optimise Material Flow in an AGV-Based Flexible Jobshop Manufacturing System with Performance Analysis"	(Fazlollahtabar et al., 2010)	Deterministic
8	"Impacts of Quality and Processing Time Uncertainties in Multistage Production System"	(Wazed et al., 2010)	Statistical
9	"An Integrated Performance Driven Manufacturing Management Strategy Based on Overall System Effectiveness"	(Nicholds et al., 2018)	Other
10	"Standard WIP Determination and WIP Balance Control with Time Constraints in Semiconductor Wafer Fabrication"	(Kuo et al., 2008)	Deterministic
11	"Tractable Nonlinear Production Planning Models for Semiconductor Wafer Fabrication Facilities"	(Asmundsson et al., 2006)	Analytical
12	"Lot Cycle Time Prediction in a Ramping-Up Semiconductor Manufacturing Factory with a SOM–FBPN-ensemble Approach with Multiple Buckets and Partial Normalisation"	(Chen et al., 2009)	MLB
13	"Simulation-Based Optimisation of Dispatching Rules for Semiconductor Wafer Fabrication System Scheduling by the Response Surface Methodology"	(Zhang et al., 2009)	Other
14	"Performance Prediction and Evaluation Based on the Variability Theory in Production Lines Using ARENA Simulation"	(Li et al., 2018)	Statistical
15	"Towards Zero-Defect Manufacturing (ZDM)—A Data Mining Approach"	(Wang, 2013)	Statistical
16	"Manufacturing Intelligence to Forecast and Reduce Semiconductor Cycle Time"	(Chien et al., 2012)	MLB
17	"Performance Improvement of a Multi Product Assembly Shop by Integrated Fuzzy Simulation Approach"	(Azadeh et al., 2012)	Other
18	"Estimation of the Mean Waiting Time of a Customer Subject to Balking: A Simulation Study"	(Jang et al., 2007)	Other

The study revealed the following calculation types:

A) Analytical Models

Analytical models use methods based on mathematical equations. These models can be used to predict the behaviour of certain elements of a system and understand the current behaviour of a system. Thus, they can be used for both use cases of performance measurement and performance prediction. Analytical models use mathematical functions to express unique relationships between variables. A function is a map that takes values from the domain set and transforms them into values from the range set. Per calculation instance, a function can only return one value (the value for the dependent variable), whereas the input parameters (the independent variables) can be any value. Functions can be characterised as linear and non-linear. Linear functions express a direct proportion between the input variables and the function value and only return a value from the range set once. Non-linear functions usually do not express a direct proportion and may return the range values multiple times, and thus, a different set of input parameters may lead to the same function result. The mathematical basis for many analytical models is the application of queuing theory. Queueing theory is defined as a mechanism to reflect the length of time that a product waits to be produced. Queue length times are calculated based on the speed that a service-providing unit operates and the number of requests to be processed. The formula for determining the average response time for a transaction is known as Little’s Law and is mentioned in section 4.3 as the foundation for several KPIs (Caliri, 2000). In the case of a performance prediction, a function is considered to represent a specific KPI. The calculated value is then dependent on the given input parameters, or more precisely, quantified attributes which specify a process at a certain point in time. To study different scenarios and to gain a broader set of results, the calculation is executed several times using varying input parameter values.

B) Statistical Models

Statistical models are a technique in mathematical statistics and are usually specified by mathematical equations. Though there exists no general definition in literature, a statistical model is commonly described by two sets *S* and *P*. *S* is the set of possible observations from a process, and *P* is the set of probability distributions on *S*. The set *P* is mostly parametrised (McCullagh, 2002). Statistical models are used to test statistical hypotheses against sample data. The calculated results of a statistical-hypothesis test are not certain. Therefore, the chosen significance level and the probability distributions according to the sample data are used to reduce the number of wrong decisions against the hypothesis. In contrast to results from analytical models, these prediction values must be possible values with a certain degree of probability and within a certain error interval. A test procedure generally begins with the formulation of the null hypothesis H_0 and the alternative hypotheses H_A. To gain meaningful results, the next step of determining the correct probability distribution function is very important. Then, the significance level must be selected prior to the observation of the sample data and the definition of the critical region. Based on the sample data, the observed value t_{obs} is calculated from the test statistic T. Finally, a decision must be made whether to reject $H_0$and consequently accept H_A or to not reject H_0. The rule for this decision states that if t_{obs} is in the critical region, the null hypothesis must be rejected. In addition to hypothesis testing, there exist other methods to gain statistical results, such as Markov chains.

C) Machine-Learning–Based Models

Machine-learning–based (MLB) models use methods and techniques from the discipline of machine learning. It is a term used in the artificial-intelligence community to indicate automated improvement based on experience or empirical data in accomplishing a given task, such as optimising an objective function (Gass and Fu, 2013). The following learning types are described in the literature (Awad and Khanna, 2015):

- Supervised learning: A learning mechanism is trained by pre-labelled input data. The label attribute value is the value that must be predicted. Thus, the learning mechanism must synthesise an accurate model function that attempts to generalise the relationship between input data (so-called *feature vectors*) and the predicted output (so-called *supervisory signals*).
- Unsupervised learning: To discover hidden structures in unlabelled datasets, unsupervised learning mechanisms are applied. Typical use cases are data compression, outlier detection and classification. The primary goal of such models is to reveal unknown relationships.
- Semi-supervised learning: These algorithms use a combination of a small number of labelled and a large number of unlabelled datasets to generate a model function. The model goals tend to be those of

supervised learning; however, they involve reduced human effort in labelling the masses of data.

- Reinforcement learning: This methodology uses a control-theoretic trial-and-error learning paradigm with rewards and punishments associated with a sequence of actions. A machine may autonomously reconfigure its future actions using past experiences of observable changes in the state of its environment.
- Inductive inference: Based on training datasets, the learning mechanism identifies general rules that represent the hypothesis space. The rules can then be applied to specific test cases to obtain a prediction. With continuously new datasets, the generalisation process may be an ongoing task to develop a richer hypothesis space.
- Transductive learning: This learning mechanism attempts to predict exclusive model functions for specific test cases by using additional observations that are related to the new cases. Compared to the inductive inference, no generalisation takes place. Knowledge gained from specific training datasets is only meant to be applied to other specific test datasets.

The MLB category includes, for instance, all models which use artificial neural networks, support vector machines or DM methods.

D) Deterministic Models

Deterministic models are built on the assumption that changes in an environment are based on fixed parameters with no uncertainty, compared to statistical models, for example. If the environment is, for instance, a certain population, there are fixed parameters such as the selection coefficient, mutation pressure and migration (Rédei, 2008). Compared to analytical models, which usually also have a deterministic character, the deterministic models are not employed with the development of mathematical functions but with the development of algorithms. This can be achieved, for instance, through the application of imperative programming. As in any modern programming language such as Java or C#, the procedures or functions may have either an evaluative or an acting character. In either case, using a given set of input values, the model will always return the same result. Deterministic models process only in one direction. This means there are no feedback signals within the model structure which would influence the process or the results. In control theory, such models are known as open-loop controllers. A model can be formally defined by an ISO-normed flowchart that includes at minimum the respected input parameters, the desired output and the actual operations and decisions. The flowchart is a graphical representation of an algorithm, which is defined as a finite set of well-defined rules that specifies a sequence of operations for performing a specific task (Weik, 2000). Deterministic models are principally time-independent, and thus, the input and output must be interpreted as an occurrence at a single point in time.

E) Other Models

The *other* category collects the types of models which do not match the criteria of the previously discussed categories. In this research project, the PPES and PdMSM would be classified as *other*. PdMSM is mainly characterised by the principles of cybernetics and overlaps with deterministic characteristics, such as a fixed set of input and operations. However, it uses time as an important model dimension and allows feedback loops within the model structure. From a control-theory perspective, this is called a closed-loop model. PPES has some attributes from inductive learning, such as the rule-based knowledge database, however, it applies a deductive reasoning approach. Further calculation types which are sorted into this category are decision trees and general simulation.

These models differ not only in their core calculation type but also in their concrete prediction goals. There are several perspectives how to gain improvement in production performance. The following categories of perspectives could be identified in this research:

- To solve challenges from a **logistics** perspective
  Example: To predict the effect of changing lot sizes
- To solve challenges from a **quality** perspective
  Example: To predict production yield based on changing influences
- To solve challenges from an **automation** perspective
  Example: To predict the benefits of applying automated wafer handling
- To solve challenges using **patterns and causal relationships**

Example: To predict production performance using artificial neural networks

- To solve challenges from a setup or **maintenance** perspective
  Example: To predict production performance with varying scheduling policies

Table 4-3 shows the number of models per calculation type and perspective as previously described.

Table 4-3: Study Results Per Calculation Type and Perspective

	Analytical	Deterministic	MLB	Other	Statistical	Sum
Automation	1					1
Logistics		4	1	2		7
Patterns and causal relationships	1		2	3	1	7
Quality					2	2
Setup or maintenance					1	1
Sum	2	4	3	5	4	18

Beyond the chosen calculation type and perspective, there are further aspects for evaluating the models according to their possible application to this study. The analysis will inspect which input and output parameters are given per model, whether the examined environment is scalable and whether the model parameters are extendible to support this research project. The input parameters of the model refer to selected control factors to predict performance indicators as model output. The models were analysed based on the referenced literature to find out whether input or output are extendible. The set of parameters of a model is considered to be extendible, if further input or output parameters can be integrated with the model. Input is only marked as extendible, as long as the additional parameters have effect on the prediction results without the need of a model redesign. If a model would have to be redesigned to make use of the additional parameters, for instance, by changing equations, it is not considered to be extendible. Output is marked as extendible, if a model would produce results for additional KPIs, which could be extracted without a model redesign. An environment of the model is marked as scalable, if, for instance, the number of workcenters or operations can be increased or decreased without a model redesign but only via configuration of the existing set of input parameters. Table 4-4 lists the results from this analysis:

Table 4-4: Model Analysis by Possible Application

#	Model Input Parameters	Model Output	Parameters Extendible	Environment Scalable
1	Paper not accessible, therefore, no analysis possible.	N/A	N/A	N/A
2	Historical WIP level; historical move volume; disruptive factors (machine breakdowns, preventive maintenance, operator absence, etc.)	Future WIP level, future move volume	No	No
3	Number of required components in automatic stage, production rate per component, demand rate, setup cost per cycle, holding cost per component, holding cost for an end product, shortage cost for an end product, defective rate per component in automatic stage, defective rate of end product in manual stage, rework cost for a defective component, rework cost for a defective end product, time period within which inventory of a component depletes, time period within which inventory of the end product depletes, time period within which backorder is replenished, CT, maximum inventory level per component, maximum inventory level of the end product, maximum backorder level of the end product	Costs per unit	No	No
4	MTTR (short and long); job release policies (shift release, CONWIP, WIPLOAD control); dispatching policies (first in, first out; earliest due date; critical ratio); batching policies with different wait times	CT, WIP, lateness, fab output	No	No
5	Lot size policies, fab capacity	CT, GR, wait time	No	No
6	Scheduling policies such as cyclic, longest queue, shortest queue	GR	No	No
7	Completion time per production step, processing time of a shop per product, transferring time between shops, velocity of automated guided vehicle, distance for product between shops, waiting time for product per shop, cycle time for product, total working time per day	GR	No	Yes
8	Batch size at the bottleneck station, setup time, CT	Lead Time, WIP	No	Yes
9	Average line staff, labour hours per unit, maximum output capacity, maximum and average finished goods stock levels per year, expected stock out days per model per year	Overall system effectiveness	No	Yes
10	WIP level and queue per workstation, inter-arrival time and service time of material, arrival rate, number of	WIP	No	Yes

	machines per workstation, availability rate of workstation			
11	Production plans, WIP, inventory, capacity, lead-times per workstation	GR	No	Yes
12	Historical data on normalised CT per lot, normalised CT forecast per lot, utilisation, lot release time, WIP, total queue length, total queue length before bottlenecks, total queue length in entire factory, wait time, future discounted workload on processing route, prediction error per lot, prediction error rate per lot	CT	No	No
13	GR-relevant aspects (e.g., dispatch-rule parameters)	CT, WIP	No	No
14	Arrival coefficient of variation (CV) of the products, process CV, line CV, number of tandem stations, number of parallel machines at a station, set of parallel machine numbers at each station, buffer size between two adjacent stations, batch size of product waiting for processing, standard deviation of natural processing times at a station, standard deviation of the effective processing times at a station, MTTF, MTTR, CT, A_{Tool}, expected waiting time spent in queue, WIP, GR, arrival rate of the product, departure rate of the product, time required to process a single product, average natural processing times at a station, effective mean processing times at a station, time indicator of product arrival, parameters which indicate lower limit, peak location, upper limit of triangle distribution, shape parameter of the gamma function, rate parameter of the gamma function	GR	No	No
15	Visual pattern projection	Yield	No	No
16	WIP, capacity, utilisation, average layers, GR	CT	No	No
17	Historical data on process operations	GR	Yes (input)	No
18	Statistical values on arrival and serving times	Wait time	No	No

4.6 Summary

This chapter has provided a comprehensive overview of the various aspects of PS performance in the SI PS. Different methods of defining a PS have been presented, and the most proper definition for this research project has been determined, which is a cybernetic perspective. The problem of inconsistent evaluation of PS performance has been discussed and resolved for this thesis. PS performance will be evaluated from four perspectives: (1) logistics, (2) quality, (3) engineering, and (4) maintenance. These perspectives are related to the challenges in SI value chains that could be mastered by PA as proposed by the conceptual framework in Chapter 2.

The primary measures have been discussed, including the underlying formulas and relationships between measures. These measures are important for the PPES and PdMSM that will be developed and evaluated in this thesis. The PM review has presented a concise view of applications, parameters, calculation types and structural flexibility for the models, which have been identified as relevant to this study. Further, the underlying core methods have been classified by distinct calculation types. The review has also revealed that none of the relevant and published models has been employed to investigate PS behaviour from the perspective of PA. Due to the selected type of calculation, most of the models are not extendible to serve scenarios other than those initially intended. The model review has further shown that the fundamental associations and effects between PA and SI PS performance have not yet been analysed. Thus, this review supports the importance of this study, which is explicitly employed to investigate the impact of PA on the SI PS performance.

Chapter 5 Data Collection and Presentation

5.1 Introduction

5.1.1 Introduction

To investigate realistic and meaningful impacts of PA on SI PS performance, the knowledge of the fundamental components, associations, and effects within a SI PS is required. As discussed in Chapter 4, most performance models are concerned with the established associations from Little’s Law and its application for calculating the operating curve. However, these models do not contain all the required data and cannot be directly applied to calculate potential benefits of PA. Therefore, the missing components, associations, and effects must be produced and analysed first. In this chapter, the data collection is presented that was conducted at a wafer fabrication facility of the case study company.

5.1.2 Case Study Company and Products

The company selected for the case study is one of the international market leaders in semiconductor-based illumination, visualisation, and sensor technology. Its business covers automotive, mobile, general lightning, and industrial applications. The final optoelectronic products are distributed to original equipment manufacturers to assemble high-end technology components, for instance, infrared distance sensors in cars or iris scanners in smartphones. Furthermore, typical products are car interior and exterior lights, smart illumination for horticulture and street lighting. The parent company employs over 24,000 people in Europe, Asia, and the United States and generates revenue of €1 billion.

5.1.3 Aims of Data Collection

The case study is used to collect, analyse, and evaluate critical data to understand the overall manufacturing process, performance criteria, and causal relationships between PS elements and EM challenges. The data consists of the unique associations between influencing and influenced terms. This data is used as the basis for the PPES as well as for the PdMSM. The data were collected from the following sources:

- Expert interviews
- Business process documentation
- IT system landscape documentation
- Historical data from IT systems

Since the focus of this project is on the maintenance and production processes, in this chapter the data that are concerned with the following problems has not been collected:

- The empirical relationships between KPI results and corrective actions by the management and the consequences that these would produce over the following periods.
- Simulations of production cost impacts for the questions such as "How much monetary savings can I expect when I reduce the WIP by a specific percentage?"
- Simulations of other impacts beyond EM methods on PS performance.

5.2 Data Collection Preparation

This section presents the fundamental preparation of the data collection, the design of the questionnaire, and the selection of the experts.

5.2.1 General Preparations

The first step is to present the topics and objectives of this project to the related functional department managers. It is necessary to convince them that this project would bring benefits to the company in order to obtain official support. The followings are the main benefits for the company:

1. The topic of PA in the context of big data is significantly relevant to semiconductor manufacturing; furthermore, a quantitative model for analysing the potential benefits would help to identify the most critical PS elements.

2. The methodology is generic and can be either directly applied or further developed if the PS or parameters (e.g., capacity or new product technologies) are modified in the future.
3. The methodology can also be applied to other production sites with minimised configuration efforts.
4. The general ability of the company to understand and evaluate modern technologies is enhanced and the dependencies on external consultants are reduced.

5.2.2 Selection of the Experts

On approval of the case study, the second step was to identify the most appropriate participants for the expert interviews. The selection criteria of the experts is principally based on their company role and specific work experience. Figure 5-1 presents the organigram of the related business functional departments of the case study company.

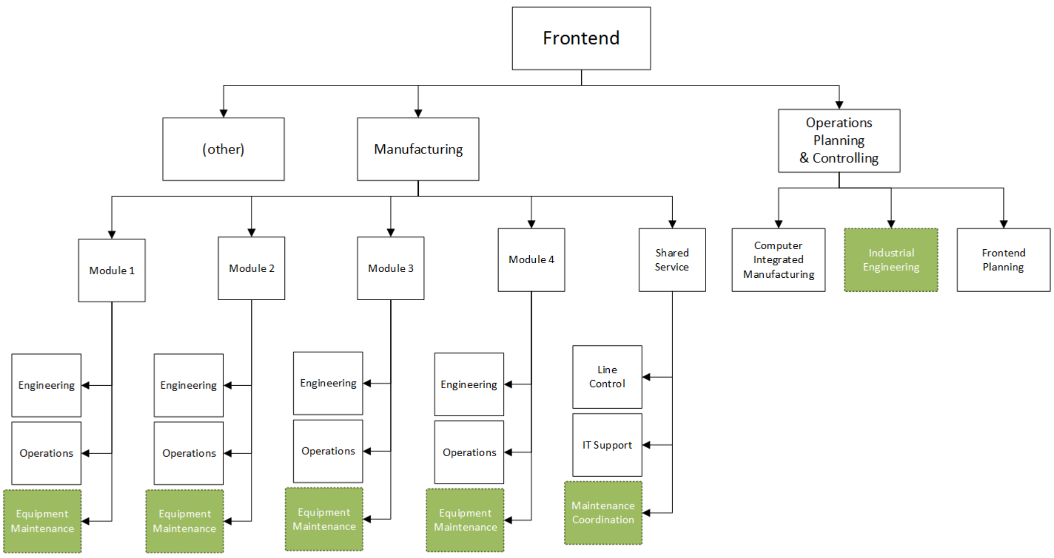


Figure 5-1: Company Organigram (partial)

From the figure, it can be seen that the frontend production area is divided into several major departments, each of which is again split into subgroups. The relevant groups for this case study are organized within the manufacturing department and the operations planning and controlling (OPC) department. All PS performance experts are consolidated in one group under

OPC. These are the IE experts. The operational EM experts are divided into several manufacturing modules. The strategic EM experts are consolidated in a so-called shared service centre. The green boxes in the organigram are the relevant groups for the case study.

The organigram and its identified sub-departments is used to decide the number of potential experts for this study. Furthermore, the selection of experts has been discussed with the department heads for their approval. Finally, 13 experts were identified to support the case study. Two of them rejected participating because of personal reasons. Table 5-1 lists the participating experts and their expertise.

Table 5-1: Selected Experts and Expertise

Expert	Expert Area	Expertise
1	IE	• General front-of-line processes • Grinding and polishing processes • Lithography processes • Chemical processes • Cluster tools • Batch processes in combination with time loops
2	IE	• Sputtering tools and processes • Evaporation tools and processes • Bonding, baking, and atomic layer deposition technologies • Plasma processes and tools
3	IE	• Entire frontend production
4	IE	• Sputtering processes, especially cluster tools • Measurement equipment and processes • Wafer probing equipment and processes • Chip dicing equipment and processes • Ageing analysis equipment and processes • Optical control equipment and processes • Volume and capacity planning for new products after the development phase
5	IE	• Entire frontend production
6	IE	• At tool level, especially cluster tools for simulation • Other applications for the entire frontend production
7	EM	• All types of equipment except end-of-line (e.g., wafer probing), including epitaxy, evaporation, sputtering, lithography, and many more.
8	EM	• Equipment, particularly in automotive production processes • Lithography equipment, especially cluster tools • Equipment for chemical processes
9	EM	• Equipment in epitaxy and analytics processes • Robots for automated wafer stock handling
10	EM	• Equipment for laser-based lift-off processes • Equipment for laser-based scribing and breaking processes
11	EM	• All types of equipment for end-of-line processes, including wafer probing, automated optical inspection, laser-based wafer dicing, taping, and many more.

As a prerequisite to collecting personal data from interviews, the workers' council has to be informed to request its official approval of the interview. During a meeting with the data protection committee, the research project was presented along with the goals and case study as a core method. In addition, the two questionnaires were discussed to clarify potential critical information. Finally, the committee approved the case study and released a company agreement. However, there were some constraint conditions, such as the agreement only allowing the interviews to be recorded in writing and not in voice recording. Moreover, all of the interviewed experts have to remain anonymous, and thus, the published data cannot include any details that would link the answers to any individual person.

Before the formal interview, all identified experts were invited to a short kick-off meeting. In this meeting, the research project and essential goals were summarised and the aims of the case study and interview contents were presented. The experts were provided with the opportunity to clarify any questions or raise concerns about the interviews. Thus, the formal interview focussed on the interview questions. Furthermore, the selected experts knew the other experts taking part in the interviews.

5.2.3 Design of the Questionnaires

To consider the particular areas of expertise, two different interview questionnaires were prepared: one IE-oriented and one EM-oriented questionnaire. Both questionnaires consist of ten questions and start with a question about the personal experiences with either IE or EM methods. This acted as a warm-up and linked the interviewee's personal background to the research project. Due to the semi-structured interview approach, succeeding questions were dependent on the particular answers of previous questions. Thus, the single interview results can differ in content and size. For instance, each IE expert must state relevant performance factors based on his/her personal experience. In a later question, the expert must define logical associations between these factors that he/she has stated previously. The main goal of the questionnaire is to identify the relevant PS elements and performance factors and how they are associated with each other. These elements and factors can be at factory and machine level.

For the interview, it is most important to design an answer schema that is generic and extendible. This semi-structured approach helps to keep the expert answers aligned between the different appointments without losing the opportunity to add personal experiences. However, if an interviewee was not able to be convinced by the answer schema or was unable to follow the schema, the schema could be rejected for that particular question and the answer be recorded as plain text. Therefore, the applied data analysis methods have to be suitable for the deviations in the answer schemas of EM and IE.

5.2.4 Experiences from a PdM Pilot Project

Independent from the case study, the manufacturing department initiated a small PdM pilot project. This provided a good opportunity to add these experiences to the thesis project and use them for the model design. The experts involved in the pilot hold the following roles in the company:

- **EM Engineer**: A technical expert for a specific group of production machines that were analysed during the pilot project.
- **Data Scientist**: An expert on PA methods and their applications in machine sensor data with an academic background in mathematics.
- **IT Engineer:** An expert in big-data analytics software that was used to implement the PdM use case.

The experts took part in a combined interview session to answer questions about their general and technical background, project intentions, results, and experiences. Because the background information prior to the appointment was highly limited, the technique of an unstructured interview has been selected. Thus, only a few major questions were prepared to focus on the pilot project contents and to allow open responses from the interviewees. Afterwards, some documents, such as management presentations and data results, were shared to use their contents for the thesis.

The pilot project was initiated one year before the case study. At the time, the company was already working on a global solution to optimise the production yield and increase the traceability of manufacturing issues along the overall process. This solution employs PA methods to obtain new patterns from data and derives recommendations for engineers and managers on how to improve the yield. To support the PA methods efficiently, a suitable software package is required to create analytical models and to apply the methods in an automated fashion. However, such a software package was not part of the company's IT portfolio. Therefore, an IT project has been initiated in parallel to select a professional big-data analytics software package from the market and to procure, install, and configure it for first use cases. After the first PA project was completed, the responsible persons from the IT department searched for other opportunities to demonstrate the capabilities of PA. During an in-house workshop on big-data technologies, the experts came together for the first time and planned the pilot PdM project.

The analysed machine group is part of the production area 'physical deposition', and performs thermic evaporation of metals. The single evaporation chamber of a machine consists of a dome for calottes with wafers, an e-gun for evaporation of the material, and an ion beam source with a filament. Figure 5-2 presents a schematic of an evaporation chamber and its components.

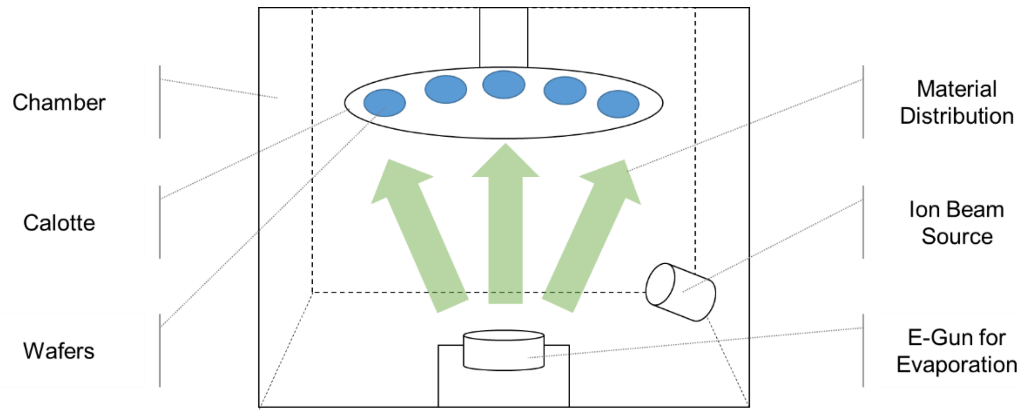


Figure 5-2: Schematic of the Evaporation Chamber (own visualization)

The central component that is analysed using PdM methods is the filament within the ion beam source, which may break on occasion. The ion beam source transforms argon as a raw material into single ions through the filament. Because, thus far, no method exists for predicting breakage, it typically occurs during a production process. This means, however, that the affected single process cannot accomplish the intended quality of processed wafers. Therefore, the goal of the PdM activity is to predict the point in time when the next filament breakage is most likely to occur, and then replace it prior to the breakage and between the value-adding processes.

The data are exported from the CIM database and consist of alarms, equipment-specific variable values, equipment events, and equipment downtimes. Because CIM uses a relational Oracle database, the data are collected, prepared (e.g., handling NULL values), and exported via SQL to a CSV file. The responsible data scientist mentioned that the SQL programming was challenging because of his lack of knowledge about the concrete database model. The raw data are imported via CSV into the analytical modelling software. Here, further data preparation procedures are applied, such as how to handle different floating number formats. The target variables such as temperature, pressure, gas flow, and voltage are selected, which should be predicted by applying PA methods. The modelling software allows the use of different methods as well as comparing the prediction quality based on test data. The aim is to find patterns in the variables that might potentially lead to filament breakage. Finally, the model can be used to monitor the physical deposition machines online using the patterns as well as trigger an alarm for the responsible EM engineers. The following features were identified as highly relevant for filament breakage:

- Cathode current level distinction in high and low etch recipes
- Recipe types (mix of etch intensities and evaporated alloys)
- Discharge voltage level prior to an unscheduled downtime
- Type of power supply unit

In addition, some patterns could be recognised when comparing expected data with suspicious data. One example was the expected cathode current versus a suspicious cathode current during the etch conditioning phase. Although features and suspicious patterns could be found, the prediction quality remained low and the model could not be used to reliably trigger filament replacements. To increase the reliability, the experts needed to define an approach to determine the optimal cut-off value and define how to handle equipment standby time or non-etching recipes. This could not be achieved during the pilot project. A further challenge was to specify the target timeframe when an EM engineer should be notified about the probable downtime of a machine in future. Typically, the wider the configured timeframe the less reliable the prediction. The involved data scientist indicated that different PA methods should be applied to prove the prediction quality before any productive usage. At least one unique characteristic for identifying filament breakages that was not known before could be detected.

Common feedback from all experts was that the effort for data preparation was extraordinarily high compared with actual PA modelling. To restrict the number of relevant characteristics in the data, it was necessary to involve process engineers who understood the single processes on the machines. Selecting relevant characteristics and reducing the dimensions of the datasets were time-consuming but a crucial part of the pilot project; this was also proved by passing a complete data dump to a student research group from the local university. The aim was to allow the students attempt to find meaningful patterns in the data without any machine or process knowledge. The students were ultimately unable to derive any valuable pattern. The project members concluded that data preparation based on deep process understanding is a mandatory step for successful PA activities.

5.3 Data Collection

This section presents the data collection process during the case study. Furthermore, it discusses the experiences of the interviewed experts in terms of applied methods in IE or EM. Each expert interview was conducted as a face-to-face meeting in a closed office room at the case study company. The total time spent on all the interviews was about 18 hours, excluding any of the preparation or analysis. Table 5-2 presents the interview dates and the duration of each interview.

Table 5-2: Interviews – General Overview

Expert	Area of expertise	Date of interview	Duration (min)
1	IE	17.04.2018	115
2	IE	18.04.2018	124
3	IE	19.04.2018	95
4	IE	24.04.2018	90
5	IE	23.05.2018	93
6	IE	28.05.2018	101
7	EM	03.05.2018	68
8	EM	08.05.2018	88
9	EM	09.05.2018	35
10	EM	14.05.2018	65
11	EM	22.05.2018	52

EM experts were asked about their concrete experiences, particularly those focussed on data-based methods such as PdM. The applied methods of the interviewed EM experts are listed in Table 5-3.

Table 5-3: Applied Methods of EM Experts

Expert	Applied EM Methods
7	• Time-triggered/interval-based maintenance plans • Partially usage-dependent maintenance plans • Widely used: 'fire-fighting mode'. This is partially planned (e.g., in laser dicing equipment) because the components are non-repairable and the risks are very low. • Indicator-driven maintenance based on equipment status that is generated from CIM software • Communication and control of maintenance actions via an 'equipment-down list', an in-house developed HTML overview, which is currently being replaced by a SAP standard solution.
8	• Participated in a pilot project for PdM from previous job in the automotive industry • Condition-based maintenance, such as monitoring equipment states via sensors and applying systematic analysis on data to prove conditions • Statistical analysis of data, including outlier analysis and pattern recognition for equipment states • Use of an envelope detector for determining a violation of a given specification from reference-run data • Post-processing 'offline' to recognise new patterns for scrap reduction during a production route (e.g., different process and machine combinations) • Time-triggered/interval-based maintenance plans
9	• Time-triggered/interval-based maintenance plans • Parameter-based maintenance plans (e.g., based on the number of runs on an epitaxy machine, sum of kilometres in transportation, and number of clock rates in valves) • Measurement value-based maintenance plans (e.g., increasing the rate of power consumption for pumps) • State-based maintenance plans (e.g., specification violation of pressure values in particulate filters can be used to predict the point in time when it will crash)
10	• Time-triggered/interval-based maintenance plans • Application of ERP software maintenance plans • Reactive maintenance where applicable • Comparison of historical data from equipment of similar types to gain new insights about failure patterns (e.g., the lifecycle of laser-based equipment). This is especially required if the machine itself does not yet write any state information
11	• State-based maintenance plans (usually manual state identification) • Time-triggered/interval-based maintenance plans

A wide range of methods exists in the area of PS performance management. Therefore, the questionnaire is designed to collect the experts' concrete experiences of these methods. The applied methods of the IE experts are listed in Table 5-4.

Table 5-4: Applied Methods of IE Experts

Expert	Applied IE Methods
1	• Equipment performance measurements: MTBF, MTOL, and OEE • WIP deviation and line profiles • Operating curve • Variabilities • Synchronicity of 4M • Compliance with the dispatching tool • Control of production rework rates • Number of moves over equipment or aggregations
2	• Golden tool matching (e.g., identifying fastest or optimal equipment for a certain process and improving low-performing equipment according to the golden tool) • Shop floor reporting • Equipment uptime variability
3	• Equipment uptime analysis • Equipment downtime gap analysis • Reduction of unscheduled equipment downs • Process stability (e.g., controlling recipe and measurement parameters from statistical process control software and reducing the variability of process results for the same recipes) for epitaxy tools • Reduction of equipment standby time through increasing operator availability • WIP balancing via dispatching software • Flow factor analysis in relation to factory utilisation (performance evaluation via operating curve) • Cycle time spread (variability) to evaluate the logistics stability of a single product
4	• Equipment utilisation via the TR25 guideline • Analysis of equipment states • Performance of scheduled maintenance within planned timeframe • Comparison of scheduled vs. unscheduled equipment downtimes • Analysis of single downtimes and improvement of future equipment stability • Equipment efficiency analysis via comparison of standby time vs. productive time • Analysis of operators' way of working • Calculation of optimum number of operators (avoid standby and waiting times based on lack of operators)
5	• Operating curve management • Efficiency measurements (personal, material, and capital) • Performance management based on weighted cycle time deviation • Comparisons of planned and current values for throughput, process stability, and monthly controlling • Fab loading analysis • Flow factor and efficiency • Cost and yield
6	• Simulations of flow factor, cycle time spread, throughput, capacity, and impacts of lot start mode on production performance • Operating curve management • Linear optimisation models for lot and process scheduling • Performance comparisons of different production sites based on flow factor, cycle time spread, throughput, and capacity at workshop level • Alpha analysis (variability)

The IE-oriented interviews provide following raw data:

1) The collection of factors that have an impact on the PS performance.

2) The weighted performance influences of the collected factors on a production machine from the area of expertise of each expert.
3) The causal relationships and weighted impacts between:
    a. The KPIs of a production machine and KPIs of the entire factory;
    b. The collected factors and the factory KPIs;
    c. The collected factors with each other; and
    d. PdM applications and a production machine.
4) The rating of suggested expectations of how PdM might affect core performance in an SI PS.

The EM-oriented interviews provide the following raw data:

1) Expectations of online versus offline analytics for PdM.
2) Expected and weighted savings and benefits from transforming reactive maintenance into preventive maintenance.
3) Identification of relevant machines or machine components for PdM applications.
4) Expected and weighted impacts of PdM on the spare part inventory level, machine or component life cycle, and general maintenance operations.
5) Expectations of challenges and chances for automation of EM operations through ERP integration of PdM applications.
6) The rating of suggested expectations of how PdM might influence core maintenance challenges in an SI PS.

General feedback from the IE experts was that the causal relationships between the PS elements are partially difficult to quantify and make clear to other engineers or managers. Thus, a simulation-based PS analysis tool, including the documented effects, may help to reveal fundamental relationships prior to any corrective action. Such applications would exist beyond the question of what potential benefits might be achieved through predictive analytics. The EM experts widely agree on the benefits of PA methods, about which their expectations were optimistic. However, they also indicated the high initial effort for data cleansing or even data generation in some areas.

As discussed in 5.2, due to the company agreement, the records of the interviews are not allowed to be published.

5.4 Manufacturing Process

This section is based on the internal documentation concerning the manufacturing processes. The company owns several manufacturing sites in Germany and Asia; each site is concentrated on specific areas, for which one purpose is to bundle expert knowledge for certain technologies. The plant used in this study is responsible for the frontend process steps. The overall and high-level production processes for an opto-semiconductor device are shown in Figure 5-3.

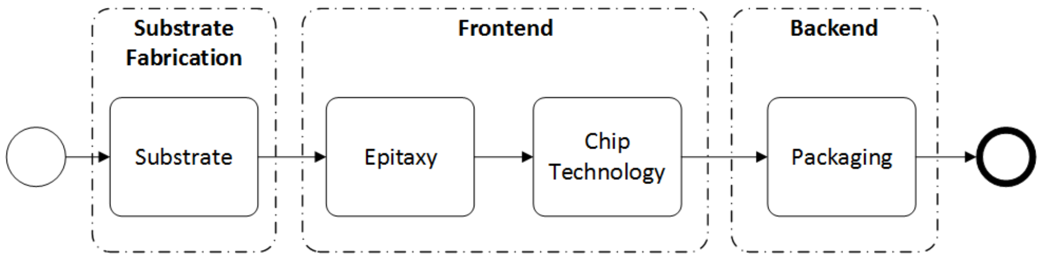


Figure 5-3: High-level Overall Production Process

The substrate fabrication itself does not belong to the actual semiconductor fabrication. Thus, the raw substrates are procured from external companies. All other frontend steps are performed in-house. Although outsourcing to subcontractor companies from single production steps up to entire products is an established method in SI (see 2.2.3), the studied company does not make use of it in the frontend area. The main reason for this is that LED and laser manufacturing in particular require much greater effort to configure, as well as to adjust equipment and recipes, in order to achieve stable processes compared with classic silicon-based products. Therefore, a further transfer to external partners is typically not useful from an economic perspective. In this study, the backend sub-process is not part of the analysis. Figure 5-4 shows the high-level frontend production process according to internal documentation at the case study company.

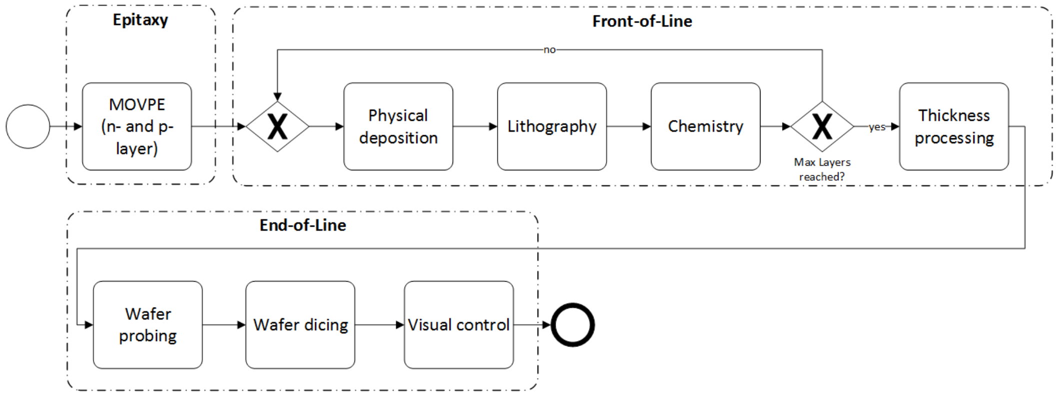


Figure 5-4: High-level Frontend Production Process

In the company's jargon, the production steps within the frontend are separated into three areas: epitaxy, front-of-line (FoL), and end-of-line (EoL). This separation is not limited to a logical grouping of processes but is also used in logistics procedures. For instance, each area has its own route or bill of materials per product. In summary, a total of over 800 machines are involved in the frontend manufacturing process, and only a few can be treated as redundant tool groups, such as for sputtering and evaporation processes. This heterogenic machine park is a significant driver of complexity. Each department in the organigram is responsible for certain areas along the frontend manufacturing process.

The epitaxy area is responsible for defining the final colour range of an LED device. Whereas silicon substrates are used for most SI products, such as CPU or RAM, optoelectronic devices do not use this type of material. Currently, the optoelectronic products use the following material systems:

- Indium gallium nitride (InGan), which has a colour range of white blue green.
- Aluminium gallium indium phosphide (InGaAlP), which has a colour range of green yellow red.
- Aluminium gallium arsenide (AlGaAs), which has a colour range from red to infrared

After epitaxy, the wafers run through a physical deposition process to create the p-contact. The metals used are usually noble metals such as gold or platinum. The following variants exist in the case study company:

- Thermic evaporation of metals
- Physical vapour deposition (sputtering of metals)
- Plasma-enhanced chemical vapour deposition
- Atomic layer deposition

The actual application in a product route depends on various aspects; for instance, the required quality. Each type of process adds layers of metal to the loaded wafers using a procedure that principally wastes the material. However, it is possible and strongly recommended to recycle a large percentage of the noble metal from the chamber walls or inner equipment parts. The recycled material cannot be reused directly but is sent to a purification company. After the physical deposition, the wafers move to the lithography area, which consists of the following sub-processes in sequential order:

- Baking
- Coating
- Stepping
- Developing

After the lithography process, the wafers run through a chemical structuring process. The actual process depends on the type of photoresist; a negative photoresist requires physical deposition and a chemical lift-off, whereas a positive photoresist requires an etching process followed by a photoresist detachment process. A typical characteristic in semiconductor manufacturing processes is the recurring lithography process. Based on technological requirements, multiple lithography layers are added to the wafers. The actual number varies from product to product. Thus, the overall manufacturing process becomes a loop until the maximum number of lithography layers is reached and all previously mentioned steps (usually with different single process configurations) are performed again. Other chemical processes that are usually required include cleaning (e.g., to remove particles), rinsing, and drying.

The final step in the FoL area is called thickness processing. Its target is to remove the bulk substrate and retain only the epitaxy layer, thereby achieving parallel surfaces and low material selectivity for all wafers.

As the subsequent and final stage in the frontend process, the wafers turn into the EoL area. Here, the main logistic difference to the previous manufacturing steps is the consideration of single chips within single processes.

The first step in EoL is called wafer probing. This process is the core method for quality control and binning; binning means sorting chips according to highly detailed product specifications, such as wavelength and brightness. After the probing, the collected data are exported from the machine to a structured file using a data format that can be processed further by analytical software systems. During the subsequent step, wafer dicing, the chips on a wafer are separated. Two established methods exist for performing this action, sawing and laser dicing; laser technology is the preferred method because of its higher accuracy. The final step in EoL is an automated visual inspection, where chips with optical defects are rejected from further processing in the backend. The effective chips are delivered to the backend plants depending on the underlying product. The backend plant creates an LED package as a saleable good for a market customer. In addition to the frontend chip as the core element, a package consists of several components for installing the LED product for further applications.

The manufacturing process described above is valid for standard types of LED product. However, depending on single product technologies, the manufacturing process is not always that linear. For certain product types based on the InGan material system, pre-processes exist that involve the physical deposition of raw substrates prior to the actual epitaxy process. A rather new product technology requires FoL processes, such as sputtering and lithography, on finished LED chips that have already passed the entire backend process. Because of the heterogenic product landscape, the PS, with its numerous processes, machines, and logistic specialities, is highly complex. As a result, many special solutions have been created either on the hardware side (e.g., for automation) or the software side (e.g., special data formats). A further speciality is the high percentage of research and development WIP at the case study plant. To develop new processes or products, production machines are reserved and blocked for normal series production. Generally, processes at this early development stage are highly unstable and affect the production flow of other products because of temporary higher priority or required stop activities.

5.5 Data from IT Systems

To configure a simulation scenario and to prove the empirical validity of the simulation model, it is necessary to obtain relevant data from manufacturing IT systems. Various software or application systems are involved. There are four levels of the systems in the case study company's internal IT architecture (where 1 means broader enterprise usage and 4 means highly machine-centric applications). Table 5-5 lists the high-level enterprise systems.

Table 5-5: High-level Enterprise Architecture Landscape

Level	Description	Tool areas
1	Enterprise logistics	■ Enterprise resource planning (ERP) ■ Enterprise quality management ■ Product lifecycle management ■ Business intelligence (BI) ■ Advanced planning and optimisation ■ Standard office systems ■ Master data management (MDM) ■ Electronic data interchange
2	Factory control	■ Sense and response ■ Dispatching and scheduling ■ Planning and optimisation
3	Manufacturing execution	■ Shop floor control (SFC) ■ Process control ■ Manufacturing quality management
4	Equipment integration	■ Equipment integration (EI), also known as computer integrated manufacturing (CIM) ■ Analytics

None of the systems really works autonomously and each is connected through data or functional interfaces to other systems. These technical connections are useful because the business processes are also connected logically. However, the number of the systems that are relevant for this study can be limited after considering those important business processes and their primary data sources. Figure 5-5 shows the most critical IT systems for this study and the data flows that connect them; it is noteworthy that no system from level two is involved.

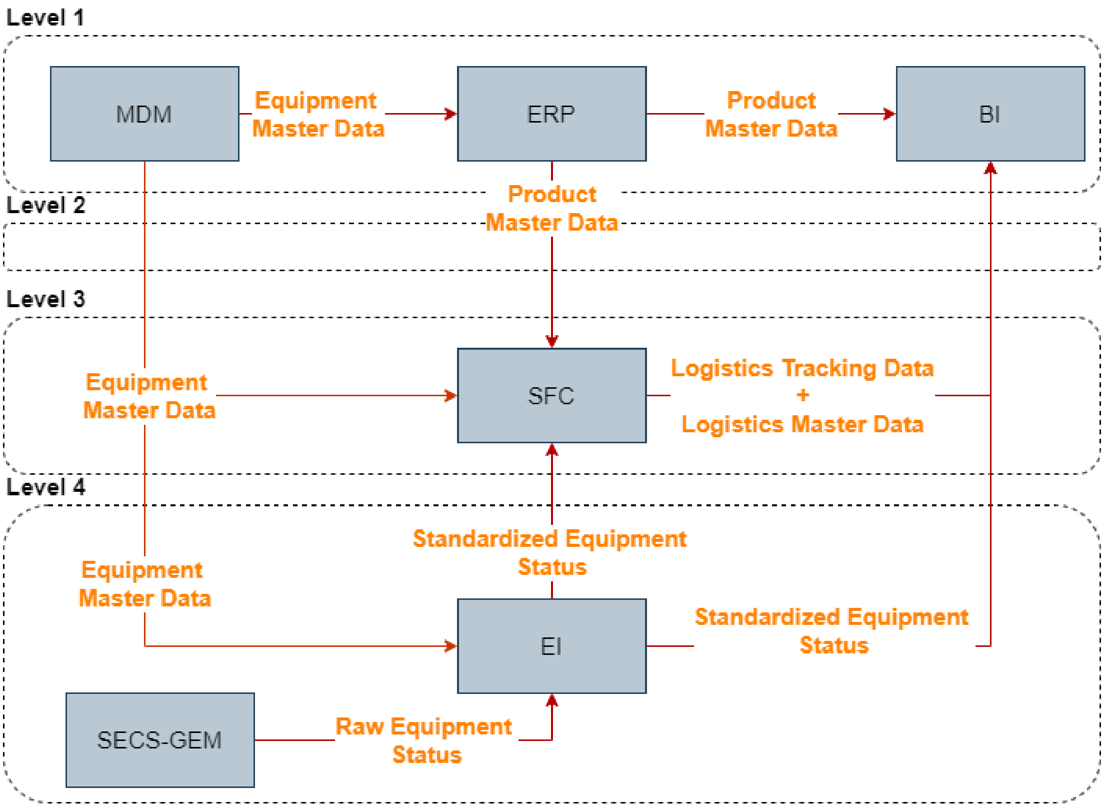


Figure 5-5: Primary IT Systems and Data Flows that are relevant to this study

Some more data routes exist between the aforementioned systems as well as to or from other systems; however, these data are not relevant to this study. The important types of data from the primary IT systems per architecture level are as follows:

1) **Equipment master data (Level 1)**: Engineers with machine-specific knowledge create these data in the central MDM, which sends the data after a finished release process to the operational systems. Equipment master data consists of logistics and process abilities, such as how many wafers of particular diameters can be processed at the same time; technical specifications, such as the constitution of multi-chamber machines, and many more.

2) **Product master data (Level 1)**: Product engineers create these data in the central ERP, which sends the data after a finished release process to SFC and BI. Product master data consists of a standard lot size, area diameter, and grid layout, as well as a plan yield per product. Further information includes multilevel product technology classifications, material status, and further logistics planning information.
3) **Logistics master data (Level 3)**: Process and IE engineers create these data within a software component of SFC. The data is directly used by the SFC itself (e.g., to generate single lot travellers) as well as being sent to BI for mid- and long-term analyses. Logistics master data consist mainly of product routes that consolidate the production sequence of single processes, recipes, process-oriented planning data, and released equipment per single process. The data records reference the product master data from ERP and the equipment master data from MDM. Logistics master data are used in BI; for instance, to generate reports on CT per product or factory area compared with the RPT from planning data.
4) **Logistics tracking data (Level 3)**: SFC creates these data by capturing process activities, which is usually performed manually by the responsible operators or automatically by involved machines. The data are sent to BI on a regular basis according to a scheduled frequency. Logistics tracking data can be stored at the lot, wafer, or chip level depending on the base unit of a single process. They consist mainly of time stamps that are referenced to certain activities, such as the start of a single process on a specific machine, or the end of it. The data are partially used in SFC to maintain control over timeframe conditions between single processes. If several single processes in a sequence are highly dependent on each other (e.g., because of chemical reactions that should be avoided), then the process time stamps can be used to monitor the remaining time. Thus, a lot can be assigned temporarily with higher priority when the timeframe condition is at risk. Logistics tracking data are used in BI to analyse various aspects of the PS performance, such as WIP per production area or FF per product technology.

5) **Raw equipment status (Level 4)**: A production machine creates these data directly during an operation and sends via the SECS-GEM interface to CIM. The raw data can differ between single items of equipment; for example, because of different machine manufacturers or equipment generations. Not all equipment is able to send data via SECS-GEM; for instance, because of missing procurement specifications in the past. In such cases, the equipment status is generated either through a software interface manually controlled by an operator or derived from logistics tracking events from SFC. This is sufficient for uptime/downtime analyses but prevents EM engineers from obtaining deeper insights into downtime patterns because of missing raw data.
6) **Standardised equipment status (Level 4)**: CIM software creates these data after transforming the raw equipment status information. The software does not push the data actively to any other system, but SFC requests it online on demand, such as when the dispatching software plans the next free equipment for a certain single process from a lot traveller. The standardised equipment status is required to support machine-overarching analyses because the single machines typically send different raw status data. The IE experts configure rules for every piece of equipment during the CIM release process to translate automatically the raw data into standardised data once the machine is productive.
7) **Historical equipment status (Level 4):** These data are sent regularly to BI according to a scheduled frequency. They are based on single standardised statuses after transformation in CIM. The data are analysed in BI according to SEMI standards to generate uptime and downtime information over a certain operating period. This information can be used to reveal critical downtime patterns or unnecessary standby periods to increase equipment capacity.

Finally, all of these data are used to analyse historical courses of KPIs, such as capacity, moves, machine uptimes, and WIP. These types of reporting data are created and stored in BI and extracted for the past year. Thus, the simulation model can be configured and approximated to the realistic courses based on these data extracts.

5.6 Summary

The case study reveals valuable insights into the research topic, which influences PA applications could generate on SI PS. A typical challenge in SI manufacturing is the heterogenic machine park as well as the process landscape. This leads to a complex PS and difficult resolution of insufficient performance indicators. In particular, in optoelectronic wafer fabrication, great effort is required to adjust the process and machine parameters to achieve a stable series production. This is the main reason why outsourcing to foundries is not profitable from an economic perspective, and therefore, the entire frontend process is performed internally.

The manufacturing process is supported by several IT systems that grew mostly independent from each other over 10 or even 15 years. Each system is optimised in special process aspects such as ERP, MDM, SFC, and equipment integration. Because the systems are managed and supported by different groups within the business and IT departments, a typical challenge is the missing standardisation between data formats, naming conventions, detail levels, and specification requirements. Major functionalities from each system are connected through interfaces to serve the production flow. However, BI and analytics projects struggle with the resulting inconsistencies, which impede the generation of standardised reports or analytical models.

Because nearly all aspects of the manufacturing process are covered by IT systems from long-term logistics planning down to equipment-internal state monitoring, missing data is not the reason for failing or postponing PA initiatives in SI. As mentioned by the experts who performed a PdM pilot at the case study company, the efforts required for data preparation were extraordinarily high compared with the actual PA modelling. Thus, the pure amount and variety of data captured by different IT systems without common standards for data generation can be seen as the greatest problem. Despite the efforts, the PdM pilot was rated as a success by the project team members because features for machine component breakage were identified that were not known before.

Chapter 6 Data Analysis and Evaluation

6.1 Introduction

This chapter presents the data analysis and evaluation for the purpose of formulating a dynamic hypothesis that will result in a CLM. This formulation is an important step in the overall modelling process and prerequisite to the PPES and the PdMSM. Sterman (2000) describes it as dynamic, because it must provide an explanation of the dynamics within a system based on the underlying feedback structure. He explains that the CLM is a hypothesis because it is always provisional and the model engineer can improve it over time as he/she learns from the real world. The results of this chapter provide the answers for RO2 to specify the causal relationships between the application of PdM and the performance-critical characteristics of an SI PS.

As discussed in Chapter 5, the interview questionnaires are designed to collect data to obtain direct effects between SI PS elements and factors, as well as expected impacts of the application of PdM on the SI PS performance. A particular group of selected experts covered one perspective each. Therefore, the consolidation of both perspectives is a significant part of the data analysis and evaluation. The raw data from the interview sessions must be analysed and evaluated to extract meaningful results for the entire research project. The secondary data gained from the manufacturing process and IT systems documentation is used in chapter 8 to shape the simulation model and to configure a particular scenario. Because the case study employed semi-structured interviews, each answer has to be analysed depending on the type of each specific question. For the more open questions, the coding method is applied in order to generate common themes between the different interview results. Such themes form the basis for the transformation of the interview results into variables as part of the advanced analysis methods. Data preliminary cleansing methods are applied to remove inconsistencies from the coded results. A potential use case is that multiple interviewees responded with the same association between terms but one group mentioned a negative effect whereas the other group mentioned a positive effect. Whereas the PPES can be used to reveal contradictory but logically correct effects through transitive impact analysis, the direct effects as primary model information must be clear. Therefore, it is necessary to define and apply rules for resolving such inconsistencies. By contrast, for rather quantifiable questions such as how much the interviewee agreed with a statement from 0 to 10, the answers can be aggregated and interpreted directly.

This chapter is organised in the following order:

1) **Analysis of the expert interviews from IE:** the effect associations between SI PS elements and other PS-relevant factors are analysed.
2) **Analysis of the expert interviews from EM:** the impacts of different maintenance strategies as well as PdM approaches on machine-oriented performance indicators are analysed.
3) **Analysis of expectations regarding PdM:** This section presents the analysis of an expectation rating for both expert groups. The predefined expectations focus on the impacts of PdM on PS- or machine-oriented KPIs.
4) **Consolidation and Evaluation:** All individual results from the previous sections are consolidated into a common CLM. The generated associations are evaluated in order to identify most influenced and influencing terms.

6.2 Analysis of Interviews with Experts in IE

Because the interviews were conducted in German, the answers were also recorded in German. This was a decision made to save time during the meetings by saving the translation for a later time. Only common English terms or abbreviations that are typically used in the company as well as in German conversation were recorded directly in English. The first step in the data cleansing stage is to translate all parts of the interview answers into English, which also provides for the harmonisation of technical terms that are either named differently or paraphrased in other words. This allows a clearer combination and comparison of terms for analysis. The harmonisation also includes a transformation of different perspectives of a term. For instance, one term that was recorded numerous times was ‘operator qualification level’. However, the interview responses differed slightly in perspectives on this term. For some of the experts, the actual operator qualification level is considered as either an impacted or impacting term, whereas for others the ‘importance of operator qualification level’ needed to be considered instead. It was crucial to maintain clear naming of such concatenated terms for the model development; this is because parts of terms such as ‘importance’ are candidates for first-order logic predicates. Thus, only the term ‘operator qualification level’ would be transformed into an atomic model variable, whereas the term ‘importance of operator qualification level’ would be transformed into a functional statement such as ‘operator qualification level has importance’. The benefit of this for the model development is that ‘operator qualification level’ remains the focus on the impact analysis, whereas ‘importance of operator qualification level’ as an atomic term would be treated as a completely different variable. The variable and predicate transformation is presented in Chapter 7.

The following sub-sections present the aggregated results from the particular interview questions.

6.2.1 Factors with Impact on PS Performance

After the data consolidation, translation and harmonization have been performed, 36 factors are identified that influence the PS performance in SI. Primary aspects such as availability and bottleneck can group the factors in order to identify crucial aspects of influencing factors. Table 6-1 lists the aspects and number of factors that influence PS performance.

Table 6-1: Identified Aspects and Number of Factors that influence PS Performance

Aspects of Factor	Number of associated Factors	Aspects of Factor	Number of associated Factors
Availability	6	Synchronicity	1
Bottleneck	5	Prediction Capabilities	1
Variety	3	Automation	1
Strategy	3	Utilization	1
Variance	2	Compliance	1
Stability	2	Orders	1
Maturity	2	Yearly Activities	1
Qualification	2		
Material Flow	2		
Transparency	2		

6.2.2 Influences of Performance Factors on Production Machines

The experts were asked to declare which of the previously identified factors have an influence on which characteristic of production machines. In addition, the significance of each influence must be weighted from 1 to 10 based on their experiences. The significance of the influence indicates to which extent a target aspect would increase or decrease if the source factor would increase. Table 6-2 lists the identified associations, the number of responses and the average weight of the influence that is called impact (mean). Because of the characteristics of semi-structured interviews, the number of responses can differ between the records. The number indicates how many interviewees experienced the same association in reality independent from each other. For records that present an association that was only identified by one expert, the mean impact value is the single impact value that was captured during the interview.

Table 6-2: Effect Associations between PS Performance Factors and Machine Characteristics

PS Performance Factor	Machine Characteristic	Number of Responses	Impact (Mean)
4M Synchronicity	Standby Time Duration	1	−10.00
Dispatcher Compliance	Standby Time Duration	3	−5.33
Dispatcher Maturity	Standby Time Duration	3	−6.00
EM Availability	Standby Time Duration	3	−6.00
EM Availability	Unscheduled Down Duration	5	−7.60
EM qualification level	Scheduled Down Duration	1	−5.00
EM qualification level	Unscheduled Down Frequency	1	−1.00
Equipment Reservations	Engineering Time Duration	1	10.00
Equipment Reservations	Standby Time Duration	3	3.33
Fab Utilization	Downtime Frequency	1	7.00
Fab Utilization	Scheduled Down Percentage	1	3.00
Maintenance Strategy	Equipment Going Rate	1	4.00
Maximum Wait Time for Batches	Standby Time Duration	1	2.00
Operator Availability	Standby Time Duration	5	−3.20
Operator Qualification Level	Standby Time Duration	2	−6.00

Process Development at Production Equipment	Engineering Time Duration	1	10.00
Process Development at Production Equipment	Equipment Capacity	3	−7.67
Process Development at Production Equipment	Unscheduled Down Frequency	3	1.67
Process Maturity	Standby Time Duration	1	−2.00
Process Maturity	Unscheduled Down Frequency	6	−5.83
Process Stability	Standby Time Duration	1	−2.00
Process Stability	Unscheduled Down Frequency	4	−8.00
Process Variety	Scheduled Down Percentage	1	5.00
Rest 3M Availability	Standby Time Duration	4	−4.00
Setup Frequency	Equipment Capacity	3	−4.67
Setup Frequency	Scheduled Down Duration	1	5.00
Single Process Variety	Equipment Capacity	1	−4.00
Tool Dedication	Equipment Capacity	3	−1.00
Tool Dedication	Standby Time Duration	2	−0.50
Transportation Variability	Equipment Capacity	1	−5.00
WIP Variance	Standby Time Duration	1	6.00
Wafer starts per week (WSPW) Variance	Risk of Equipment Bottleneck	3	2.67
WSPW Variance	Standby Time Duration	3	4.67

6.2.3 Influences of Production Machines on Performance Factors

In the same way as performance factors of the surrounding PS may influence a production machine, the machines influence the performance of the surrounding PS. Table 6-3 lists the captured associations from the interviews, the number of responses of each association and the logical impact. The interviewees did not state a weighted impact, because the effects differ from machine to machine. Without considering single machines, a numeric impact would not present a meaningful result. Therefore, the experts only mentioned the logical impact in general, where '+' refers to an increasing effect and '–' refers to a decreasing effect.

Table 6-3: Influence of Machine Performance on PS Performance

Machine performance indicator	PS performance indicator	Number of Responses	Impact (logical)
Alpha Tool	Alpha PS	1	+
Batch Size	Alpha PS	1	+
Equipment Uptime	DGR	1	+
MTBA	Alpha PS	3	−
MTBF	Alpha PS	2	−
MTBF	Equipment Availability	2	+
MTOL	Alpha PS	4	+
MTTR	Alpha PS	4	+
OEE	Alpha PS	2	−
OEE	Capacity	1	−
Performance Synchronicity of similar Machines	FF	1	−
Processing Time Variance	FF	1	+
Rate Efficiency	DGR	1	+
Scheduled Down Frequency	Alpha PS	1	+
Single Process Variety	Alpha PS	1	+
Tool Dedication	Alpha PS	1	+

6.2.4 Influences of PS Performance Factors on Factory KPIs

Each expert was asked to state which of his/her mentioned PS performance factor has an influence on the entire factory performance. The captured impact associations support the understanding of which factor affects which aspect of PS performance, in particular. In addition, the experts must weigh the declared influences. Table 6-4 presents the associations, the number of responses and the average impact.

Table 6-4: Influences of PS Performance Factors on Factory Performance Indictors

PS performance factor	Factory performance indicator	Number of Responses	Impact (Mean)
4M Synchronicity	CT Variance	4	−9.00
Degree of Knowledge of Engineers about Factory Physics	Material Flow Variance	4	−5.25
Degree of Operator Qualification Level	CT	1	−8.00
Degree of Operator Qualification Level	FF	1	−7.00
Degree of Operator Qualification Level	GR	2	4.00
Degree of Production Staff Motivation	CT	4	−4.50

Degree of Unevenness in WIP distribution	GR	1	−10.00
Dispatcher Compliance	FF	1	−3.00
EM Availability	Equipment Availability	1	5.00
Equipment Availability	FF	1	−4.00
Equipment Availability	GR	1	10.00
Equipment Reservations	Capacity	1	−3.00
Equipment Reservations	FF	1	3.00
Flexibility of Operator Qualification Level	CT	1	−8.00
High Percentage Process Inspections	CT	3	3.00
Lot Prioritizations	CT Spread	1	6.00
Lot Prioritizations	GR	2	−5.00
Operator Availability	CT	4	−6.75
Operator Availability	FF	1	−8.00
Operator Availability	GR	1	10.00
Operator Qualification Level	FF	1	−3.00
Percentage of Bottleneck Equipment	CT	3	8.67
Process Availability	GR	1	10.00
Process Development at Production Equipment	CT	1	2.00
Process Development at Production Equipment	GR	2	−6.00
Process Maturity	Equipment Availability	1	2.00
Process Stability	CT	2	−4.50
Process Stability	CT	1	−10.00
Process Stability	Equipment Availability	1	2.00
Process Stability	FF	1	−4.00
Rework	GR	1	−10.00
Single Tools	CT	1	8.00
Single Tools	Deliverability	1	−10.00
Single Tools	Line Down (Product)	1	10.00
Single Tools	Material Flow Variance	1	−10.00
Single Tools	Risk of Product Line Down	3	7.67
Tool Dedication	CT	1	7.00
Tool Dedication	FF	1	−2.00
Utilization Profile Variance	CT	1	10.00
WIP Variance	CT Variance	4	4.75
WIP Variance	FF	1	−3.00
WSPW Variance	FF	1	2.00

6.2.5 Influences between PS Performance Factors

The literature study and observations suggest that PS performance factors may influence each other. This information is important in order to generate knowledge about transitive effects using the PPES. The experts had to identify causal relations between PS performance factors that they initially mentioned, including the weighted impact. Table 6-5 presents the associations, the number of responses and the average impact.

Table 6-5: Relationships between PS Performance Factors

PS performance factor (from)	PS performance factor (to)	Number of Responses	Impact (Mean)
Automation Degree	Importance Of Operator Qualification Level	1	−10.00
Automation Degree	Operator Qualification Level	4	−6.00
Dispatcher Compliance	WIP Variance	1	−3.00
Dispatcher Maturity	4M Synchronicity	1	6.00
EM Availability	Equipment Availability	1	4.00
Equipment Availability	WIP Variance	1	−3.00
Equipment Reservations	WIP Variance	1	2.00
Operator Availability	WIP Variance	1	−4.00
Operator Qualification Level	Flexibility of Operator Qualification Level	2	8.00
Process Maturity	Process Stability	4	9.50
Process Maturity	Rest 3M Availability	1	8.00
Process Stability	Degree of Automation	1	8.00
Process Stability	High Percentage Process Inspections	3	−8.33
Process Stability	WIP Variance	1	−3.00
SCM Order Patterns Variance	WSPW Variance	1	10.00
Setup Frequency	Importance Of EM Availability	3	7.33
Single Process Variety	Setup Frequency	3	5.67
Tool Dedication	Importance Of Equipment Availability	1	3.00
Tool Dedication	WIP Variance	1	8.00
Utilization Profile Variance	Percentage of Bottleneck Equipment	1	5.00
WSPW Variance	WIP Variance	5	4.60
Yearly WIP reductions	WSPW Variance	1	3.00

6.2.6 Influences of PdM on Production Machine Performance

The experts were asked to declare their expected influence of PdM on production machine performance in general. Table 6-6 lists the influenced production machine KPIs, the number of responses that state this type of association and the average impact.

Table 6-6: Production Machine KPIs that are influenced by PdM

Machine performance indicator	Number of Responses	Impact (Mean)
Alpha Tool	4	−1.00
Degree of Production Staff Motivation	1	6.00
EM Availability	5	8.60
Equipment Uptime	5	7.00
GR	5	6.00
Material Flow	1	10.00
MTBO	2	0.00
MTOL	2	−7.50
Scheduled Down Frequency	5	3.80
Scheduled Down	1	10.00
Synchronicity Of EM Availability	1	4.00
Unscheduled Down (UD)	1	−10.00
Unscheduled Down Frequency	5	−3.00

In some cases, the logical relation between PdM and a production machine KPI can be refined. The experts considered other factors such as effect mediator that are directly influenced by PdM and that have direct impact on the machine KPI. Table 6-7 presents the mediators between PdM and the particular machine KPIs.

Table 6-7: Mediators between PdM and Influences on Machine KPIs

Machine performance indicator	Mediator
Alpha Tool	MTOL
	Reduction Of Unscheduled Down Frequency
	Reduction Of Scheduled Down Duration
EM Availability	Reduction Of Unscheduled Down Frequency
	Unscheduled Down Duration
Equipment Uptime	Optimized Maintenance Intervals
Material Flow	WIP Forecast
MTBO	Unscheduled Down Frequency
MTOL	Unscheduled Down Frequency
Scheduled Down Frequency	Optimized Maintenance Intervals

The results from the rating of suggested expectations of how PdM might affect core performance in a SI PS are presented and discussed in Section 6.4.

6.2.7 IE Data Cleansing and Consolidation

As discussed at the beginning of this section, the first activity in data cleansing is the translation of German recordings into English. The translation also considered the harmonization of similar terms to achieve a consistent vocabulary. The next cleansing work is to remove redundancies between raw terms by continuous application of the coding technique. This is crucial to generate a common denominator in order to describe the same effect recorded from different interviews. To resolve the redundancy issue, the operating curve management practices at the partner company is taken into account. The following cases of redundancy have been identified:

a) Different wording for the same meaning (e.g., 'Tool Dedication' and 'Single Tool')
b) Inadequate wording for the actual meaning in the specific context (e.g., 'Equipment Uptime' and 'Equipment Availability'
c) Different aggregation levels of the same term (e.g., 'GR' for a aggregated unit within the PS and 'Equipment GR' as particular KPI of a machine or machine group)

As a further step in data cleansing, the quantitative interview results are required to be organised into a matrix that only consists of positive and negative effects between terms. Each association between terms becomes one record of the matrix. Generally, each record of the matrix states that if the impacting term is increased, the impacted term is increased or decreased. Using this matrix, the data can be analysed against inconsistencies when the same association between terms has both positive and negative impacts. First, the interview responses of all participants were clustered by questions, including the quantitative impacts. Then, all associations between terms from all questions and the answers were consolidated into one common matrix; 120 unique associations were identified. Subsequently, a formula was applied to determine whether an association has an increasing or decreasing character. All impact values lower than zero were interpreted as ‘decrease’, whereas all impact values greater than zero were interpreted as ‘increase’. Zero is not possible as a value because the association would not exist at all. As a next step, all duplicates were removed from the matrix so that each constellation of impacting terms, impacted terms, and types of impacts only existed once. Having the data prepared at this stage, the inconsistencies can be revealed when grouping by impacting and impacted terms and the counting of occurrences. If there is more than one occurrence, there is a problem in the data and the type of impact is not unique. Table 6-8 lists the term associations that were identified as inconsistent.

Table 6-8: Inconsistent Impacts between Terms

#	Impacting Term	Type of Impact	Impacted term
1	Degree of Automation	increase/ decrease	Operator Qualification Level
2	Degree of Production Staff Motivation	increase/ decrease	CT
3	Lot Prioritisations	increase/ decrease	GR
4	Operator Availability	increase/ decrease	Standby Time Duration
5	Process Development at Production Equipment	increase/ decrease	GR
6	Process Stability	increase/ decrease	High Percentage Process Inspections
7	Rest 3M Availability	increase/ decrease	Standby Time Duration
8	WIP Variance	increase/ decrease	CT Variance
9	WSPW Variance	increase/ decrease	WIP Variance
10	Process Development at Production Equipment	increase/ decrease	Unscheduled Down Frequency
11	Tool Dedication	increase/ decrease	Equipment Capacity
12	Tool Dedication	increase/ decrease	Standby Time Duration

To make the data reliable, the inconsistency issues have to be resolved. Otherwise, the final model would not work in the expected way. It was likely that individual interviewees confused the meaning of plus or minus signs despite the explanations of the interviewer. Thus, to resolve inconsistencies, the raw data has to be searched for the affected associations to determine the most applicable sign. The method used has two procedures to identify the root causes and determine a solution:

- Outlier analysis: This looks for the majority of responses and treats the single difference as an outlier. Because of the small amount of data, even a confrontation of 2 versus 1 is seen as significant enough to decide the majority's answer. The type of impact of the outlier association is changed in the data matrix according to the majority.
- Draw: If associations between terms are rarely stated, this can lead to a draw. Here, the most applicable interpretation must be determined considering the context and logical inference. The type of impact is changed in the data matrix according to the most appropriate interpretation.

Generally, the interviewees attempted to make accurate evaluations based on their experiences; thus, the signs were neither completely ignored nor continually wrong. Deviations only appeared in a limited number of cases. Some responses consisted of comments in prose that also describe the sense of the association. Such comments helped to identify whether a sign was merely recorded incorrectly while the meaning matched other responses.

After resolving the inconsistencies by applying the discussed procedures, the types of the impacts in the data matrix are clean. Table 6-9 lists the cleaned types of impacts for the affected associations.

In addition, for the final simulation model, the signs in the raw values of each response are required to be modified. After the inconsistent records were removed and the two additional records were added, the matrix consists of 123 unique records. The matrix with the IE-oriented associations is in appendix A1.

Table 6-9: Cleaned Effects between Terms

#	Impacting Term	Type of Impact	Impacted term
1	Degree of Automation	decrease	Operator Qualification Level
2	Degree of Production Staff Motivation	decrease	CT
3	Lot Prioritisations	decrease	GR
4	Operator Availability	decrease	Standby Time Duration
5	Process Development at Production Equipment	decrease	GR
6	Process Stability	decrease	High Percentage Process Inspections
7	Rest 3M Availability	decrease	Standby Time Duration
8	WIP Variance	increase	CT Variance
9	WSPW Variance	increase	WIP Variance
10	Process Development at Production Equipment	increase	Unscheduled Down Frequency
11	Tool Dedication	decrease	Equipment Capacity
12	Tool Dedication	increase	Standby Time Duration

6.3 Analysis of Expert Interviews from Equipment Maintenance

The EM interviews were also conducted in German. Thus, the first task was to translate each answer into English. Because the EM interview questions did not focus on individual associations between a limited set of factors and KPIs, the spectrum of answers is much wider than that for IE. Due to this less structured interview, the coding techniques have to be applied for data analysis to identify logical relationships between the different answers. The first run of coding searched for common perspectives and opinions to formulate harmonised terms. Because the open answers did not directly state any association to a machine KPI, the second run of coding attempted to identify matches between the harmonised terms and suggested expectations from the questionnaire. Here, the EM experts were asked to state the impact of an expected result from PdM on crucial performance indicators. With these codes, it is possible to derive the associations between a principally open answer and concrete KPI, including an expected degree. A further step in the coding procedure is to search for logical associations between the core terms, for instance, a higher monitoring quality leading to the avoidance of machine failures. Thus, it is possible to build concatenated logical associations between core terms as well as analyse transitive effects. As a final step in the coding procedure, individual terms were transformed to express an atomic meaning based on the given association. It was crucial to limit each association between terms to simple ‘decrease’ or ‘increase’ relationships in order to generate a CLM as a basis for the simulation model (Bossel, 2004). For instance, to quantify the term ‘EM strategy’ requires indicating which aspect of the term is affected by a specific aspect from another term. A more appropriate aspect might be the ‘Maturity of EM strategy’ or the ‘Importance of EM strategy’.

The following sub-sections present the aggregated results from the particular interview questions.

6.3.1 Expectations of Online versus Offline Analytics for PdM

PdM applications may have online or offline characters. Where online PdM applications focus on high-performance monitoring of current data streams, offline PdM applications are instead concentrated on high-quality failure pattern analytics considering a larger timeframe. Though both types of applications supplement one another in order to improve the EM processes, each type may have strengths and weaknesses from a practical perspective. The experts were asked to evaluate both types based on their experiences; they were able to state more than one argument per type. Table 6-10 shows the aggregated results of the answers.

The experts stated 31 arguments in total with 17 as the offline PdM and 14 as the online PdM. Comparing the number of pro and contra arguments, offline PdM was viewed as much more beneficial than online PdM. Generally, the quality of monitoring, planning, and statistics could be improved.

Table 6-10: Comparison of PdM Online vs Offline Applications

PdM application type	Number of responses
Offline	*17*
Contra	3
Slower reaction.	3
Pro	14
Combine multiple data sources to find new patterns.	4
Find new failure patterns from single machines.	1
Higher monitoring quality.	1
Higher planning quality.	2
Higher statistics quality.	1
Independency in running analyses.	1
Prove the effectiveness of EM activities.	1
Understanding historical failure patterns.	3
Online	*14*
Contra	5
Dependency on existing knowledge.	1
Dependency on EM processes.	1
Higher data traffic.	1
Weak statistics.	2
Neutral	3
Dependency on algorithm quality.	1
High efforts to prepare data and algorithm.	2
Pro	6
Avoid failures.	2
Faster reaction.	4
Total	**31**

Additionally, the analytic models helped to understand historical failures, find new failure patterns, and prove the effectiveness of past EM activities. The experts did not expect any more negative aspects than a potentially slower reaction. Compared with the offline PdM, online PdM applications were evaluated much more diversely. In terms of positive aspects, the faster reaction on monitored abnormalities and the possibility of avoiding failures were identified. However, the experts faced challenges since their existing knowledge differs and the statistics are potentially weak. Thus, it would either affect the algorithm quality in a negative way or the EM experts would have to spend much effort to prepare the data and algorithms to cover an extensive repository of failure patterns. The analysis results imply that the combination of offline and online PdM applications would eliminate some of the weaknesses of each other, at least the weak statistics of online PdM and the slow reaction of offline PdM.

6.3.2 Savings and Benefits gained by Preventive Maintenance

Generally, PdM transforms reactive maintenance into preventive maintenance. The experts were asked what savings in terms of repair and maintenance time they expect because of this behavioural change, as well as how significant the improvement would be. It was possible to have more than one answer. Table 6-11 shows the aggregated results from this question. For savings that were mentioned by multiple experts, the mean significance is used in this table.

Table 6-11: Expected Savings by Increasing Preventive Maintenance

Saving	**Significance of saving**	**Number of responses for this saving**
MTTR	5	1
Increased speed of analysis	8	1
Increased speed of reactions	10	1
Reduced unscheduled downtime frequency	9	1
Reduced equipment downtime duration	7	5

The greatest match within the responses can be summarised as a reduction in the duration of equipment downtime. This saving can have different aspects:

- A reduction through improving planning of EM personnel and materials to ensure just-in-time maintenance activities.
- A reduction through avoiding late effects due to preventive activity.
- A reduction through avoiding collateral damage with greater impacts than the original failure.

Further savings can be achieved by increasing the speed of analysis of data as well as of reactions after abnormalities have been monitored.

In addition to the savings that can be achieved by fostering preventive maintenance, problems and costs can be reduced by minimising reactive maintenance. The experts were asked to provide from one to many expected benefits. The answers were classified by their primary benefit, and thus, answers that only transitively led to cost savings were not classified under ‘cost reduction’ but under their primary benefit. Table 6-12 shows the aggregated results.

Table 6-12: Expected Benefits from Minimising Reactive Maintenance

Benefits	**Significance of benefit (mean)**	**Number of responses for this benefit**
Cost reduction	6.6	10
Avoidance of collateral damage	5.5	2
Avoidance of total failure, foster refurbishment	6	3
EM process efficiency	10	1
Less EM staff required	6.5	2
Reduction of new equipment invests	6	1
Increase equipment lifespan	8	1
Increase EM efficiency	4.67	3
Higher monitoring quality	5	1
More efficient spare part logistics	6	1
More even distribution of equipment downtimes	3	1
Increase equipment efficiency	8.33	3
Make better use of wear limits	8	1
Reduced Equipment Downtime duration	8.5	2
Increase process stability	10	1
Rework reduction.	10	1
Overall result	6.76	17

Although the reduction of reactive maintenance can be seen simply as equivalent to the increase of preventive maintenance, the experts saw a more diverse portfolio of improvements when concretely minimising reactive maintenance activities. A possible interpretation for this result is that PdM as an enabler for reduction of reactive maintenance already leads to a tremendous improvement for a manufacturing department, even though the quality of predictions for preventive activities is not yet optimal. The benefits of highly reliable preventive maintenance can be seen as an additional benefit for the company, which can be achieved by applying PdM.

Cost reduction appears the most significant benefit with various drivers from equipment, EM staff, and EM process perspectives. The experts also saw chances of improving the overall EM efficiency because spare part demands and downtimes per shift can be controlled much more effectively than that in the current situation. Furthermore, the equipment efficiency could be enhanced by reducing downtime durations and optimising the lifespan of replaceable machine parts. Only one expert mentioned the possibility of increasing process stability. In cases of machine failure during a wafer process, the wafers typically require a rework procedure as long as they are not damaged beyond repair. Assuming the equipment failures are under more effective control, such cases could be eliminated and the overall rework rate would decrease.

6.3.3 Influence of PdM on Machine Component Performance

Because of the heterogeneous machine park and process landscape at the case study company, it is not possible or practically feasible to have one standard procedure for applying PdM to all areas. Furthermore, it is important to identify the relevant machines and their concrete components where PdM can be applied in order to gain relevant benefits. The experts considered that 18 use cases exist where PdM can be applied. Table 6-13 shows the machine component characteristics procedures for verifying the prediction quality.

The analysis shows that most of the components would not see their lifespan increase significantly. Only the handling robot, diamond scratch tool, and evaporation filament were seen as candidates where PdM would directly have a positive effect on the component itself, in addition to the surrounding equipment. A further result is that procedures exist for most of the cases to verify the prediction quality. Only two of the 18 use cases do not have either simple or accurate procedures. The existence of adequate verification procedures is a necessary criterion for starting a PdM project. The prediction algorithms must be adjusted, most probably in the early phase based on these verifications, until a long-term high prediction quality can be established. However, all of the verification procedures must be performed manually, and thus the manual effort of EM staff must be considered.

Table 6-13: Machine Component Characteristics and Procedures for Verifying Prediction Quality

Machine component characteristics	**Increase of component lifespan (0–10 / Mean)**	**Verification procedure**
Epitaxy	3	Not answered
Handling robot accuracy	10	Inspection of accuracy deviation
Mass flow controller adjustment	0	Measure tool
Metal organyl consumption	4	Weight of bubblers
Process pump current consumption	0	Inspection of current consumption
Temperature deviation for metal organyl	0	Inspection of temperature deviation
Evaporation	3.33	Not answered
Cryo regeneration	0	Not existing
Filament crack	5	Inspection of crack
Lamination	1	Not answered
Lamination knife sharpness	1	Measurement of knife sharpness
Laser Dicing	3	Not answered
Laser wear	3	Measurement of laser power
Lift-off	2	Not answered
Filter wear	2	Yes, but not specified
Lithography cluster	2	Not answered
Vacuum quality	2	Yes, but not specified
Plasma	1.5	Not answered
Exhaust blockage	0	Yes, but not specified
Turbo pumps wear	3	Yes, but not specified
Scratching	6	Not answered
Diamond scratch sharpness	6	Test prints on dummy material
Spray acid cleaning	2	Not answered
Filter wear	2	Yes, but not specified
Sputtering	1	Not answered
Shielding wear	1	Not existing
Stepping and coating	2	Not answered
Vacuum quality	2	Yes, but not specified
Thickness	2	Not answered
Filter wear	2	Yes, but not specified
Overall result	*2.62*	

6.3.4 Influence of PdM on Spare Part Stock

One of the purposes of this study is to identify whether a higher percentage of preventive maintenance caused by PdM could lead to an increased spare part stock. The reason might be that equipment components are typically not used until their life cycle ends in order to avoid equipment failures and reactive maintenance. Thus, the replacement would be required earlier to avoid a failure. Throughout a certain timeframe, the number of component changes could be higher than that in the current situation, which would possibly require more spare parts on stock. Table 6-14 shows the components where an increased spare part stock is expected after application of PdM.

Table 6-14: Machine Components with Impact on Spare Part Stock

Machine component characteristics	Minimum Stock Increase (0–10)	Maximum Stock Increase (0–10)	Increase of Spare Part Costs (0–10)
Plasma	3.5	3.5	2
Exhaust blockage	2	2	1
Turbo pumps wear	5	5	3
Sputtering	1	1	2
Shielding wear	1	1	2
Overall result	0.38	0.38	0.29

The analysis of the results demonstrates that a negative effect of PdM on the company's spare part stock is principally not expected. Only for a few tool components from plasma and sputtering did the experts see a possible stock increase, although with low impact on the associated costs. Generally, an accurate prediction of failures allows just-in-time spare part procurement. This would lead to a decreased spare part stock.

6.3.5 Influence of PdM on EM Operations

Another aspect of applying PdM is its integration into operational EM processes. The experts were asked about their expectations regarding the challenges and opportunities for automation of EM operations through ERP integration into PdM applications. One typical activity that could be transferred to PdM software is autonomously starting maintenance orders without human interaction. Table 6-15 shows the aggregated results of this question.

The results show that all experts generally wish to have autonomous PdM and ERP integration without human interaction after the stabilisation phase. PdM applications would have a significant effect on the daily operations of EM staff because decisions would be transferred from humans to the software.

Table 6-15: Expectations regarding PdM Integration into EM Operations

Expectation	Number of agreements	Number of disagreements
The PdM software shall autonomously start maintenance orders without human interaction.	5	0
If human experts are required to finally decide, it shall be only until the stabilisation phase has been closed successfully.	5	0

To evaluate how this change would be supported by the EM staff, a similar project from the past can be used as a comparison. A few years ago, a factory-wide dispatching software was introduced. Prior to that, operators had great freedom in their decisions regarding which lot box they intended to use next for their responsible process. Now, the dispatching software provides the top three lot boxes per process area, which must be processed in the exact order to fulfil PS performance targets. However, the operators did not support this new behaviour by themselves. To increase dispatcher compliance, regular monitoring has been developed to address compliance violations to the responsible managers. Although PdM and dispatching refer to a different community, it can be expected that the currently autonomous EM staff are not wholly convinced when introducing a software package that takes over the decisions. Manufacturing or EM managers must prepare such a competency change to avoid compliance issues.

6.3.6 Automation of EM Operations through PdM and ERP integration

Furthermore, despite the general intention of passing decisions to software, the EM experts stated that cases exist where fully autonomous PdM and ERP integration is not possible or useful. It was possible for them to state from one to many criteria to support these findings. Table 6-16 shows the aggregated results.

Table 6-16: Criteria for where Autonomous PdM and ERP Integration is not useful

Criteria	Expert decision due to a lack of machine intelligence	Manual inspection by EM staff required	Missing cost transparency	None	Total
Costs			1		1
Missing data	3	1			4
None				1	1
Process complexity	2	1			3
PS performance	2				2
Total	7	2	1	1	11

Most of the answers refer to a possible lack of machine intelligence that requires an expert decision. Reasons for this can be missing data, surrounding process complexity, or overall PS performance that could not be considered sufficiently by PdM algorithms. Another criterion is manual inspection that can only be performed by EM staff. This can be required because of missing data or high process complexity, such as from product-related nuances that cannot be differentiated by machine sensors. The costs were not considered the principle issue; however, one expert indicated that automatic spare part orders could lead to less cost transparency. Only one expert did not see any case in his area of responsibility where fully autonomous PdM and ERP integration would not be possible.

The results from the rating of suggested expectations of how PdM might affect core performance in an SI PS are presented and discussed in Section 6.4.

6.3.7 EM Data Consolidation

The several associations collected from the EM expert interviews were collected and harmonised to generate a data matrix similar to that in the IE case study part of the thesis. Because of the rather unstructured design of questionnaires for the EM interviews and the approach selected for the data analysis, it was not necessary to further resolve inconsistent data. The consistency checks were directly applied during the coding procedure. The EM-oriented data matrix that consists of 37 associations is in appendix A2.

6.4 Analysis of Expectations Regarding Predictive Maintenance

Both the IE and EM experts were asked for their expectations regarding PdM. The questionnaires were slightly different to those for the expert-specific knowledge. The experts had to evaluate suggested expectations using the following pre-defined patterns:

1) How much do you agree with the expectation (from 1 = do not agree to 5 = fully agree)?
2) How significant is this expectation on the production (from 1 = not significant to 5 = highly)?
3) Which PS KPI or other factor is directly affected by this expectation?
4) Which intensity of impact of the expectation on the listed KPI or factor do you see (+/− 1–10)?

In the final simulation model, the degree of intensity was adjusted by the level of agreement and importance to production. Although the intensity of an expected effect might be rated as high, this would not necessarily mean that the suggested effect would in fact apply to the SI PS. Thus, the data has to be smoothed to achieve realistic effects during the simulation study. Table 6-17 shows the mean and standard deviation of the IE expert responses on how much they agreed with the expectations.

Table 6-17: Results of IE Expectations on PdM (level of agreement)

#	Expectation	Level of agreement (mean)	Level of agreement (standard deviation)
1.	Reduction of Machine Downtimes (not the number but duration)	4.67	0.47
2.	Avoidance of Machine Downtimes (number)	3.17	1.21
3.	Harmonisation of production logistics over affected machines by production route	4.33	0.75
4.	Reduction of WIP per work centre over a fiscal year	3.17	1.07
5.	Reduction of average cycle time per work centre over a fiscal year	3.33	1.25
6.	Reduction of bottlenecks at work centres	3.60	1.50
7.	Increase in wafer throughput at work centres	3.50	0.96
8.	Increase in yield because of fewer machine-related process failures	4.17	0.90

Table 6-18 shows the mean and standard deviation of the IE expert responses on how significant the expectations are to production.

Table 6-18: Results of IE Expectations on PdM (level of significance to production)

#	Expectation	Level of significance to production (mean)	Level of significance to production (standard deviation)
1.	Reduction of Machine Downtimes (not the number but the duration)	5.00	0.00
2.	Avoidance of Machine Downtimes (the number)	4.00	1.41
3.	Harmonisation of production logistics over affected machines by production route	4.33	1.11
4.	Reduction of WIP per work centre over a fiscal year	3.33	1.37
5.	Reduction of average cycle time per work centre over a fiscal year	3.33	1.37
6.	Reduction of bottlenecks at work centres	4.33	1.49
7.	Increase in wafer throughput at work centres	4.17	1.07
8.	Increase in yield because of fewer machine-related process failures	3.83	0.90

Figure 6-1 presents a comparison between the IE experts' agreement with, and opinions of, regarding the suggested expectations' significance to production.

The deviations show the clear differences between the importance of expectations and their probability of occurrence. PdM would help to reduce the downtime duration but would not support the avoidance of downtimes in general. Among the IE experts, there is only restrained agreement that PdM directly affects PS performance indicators such as WIP, CT, and GR.

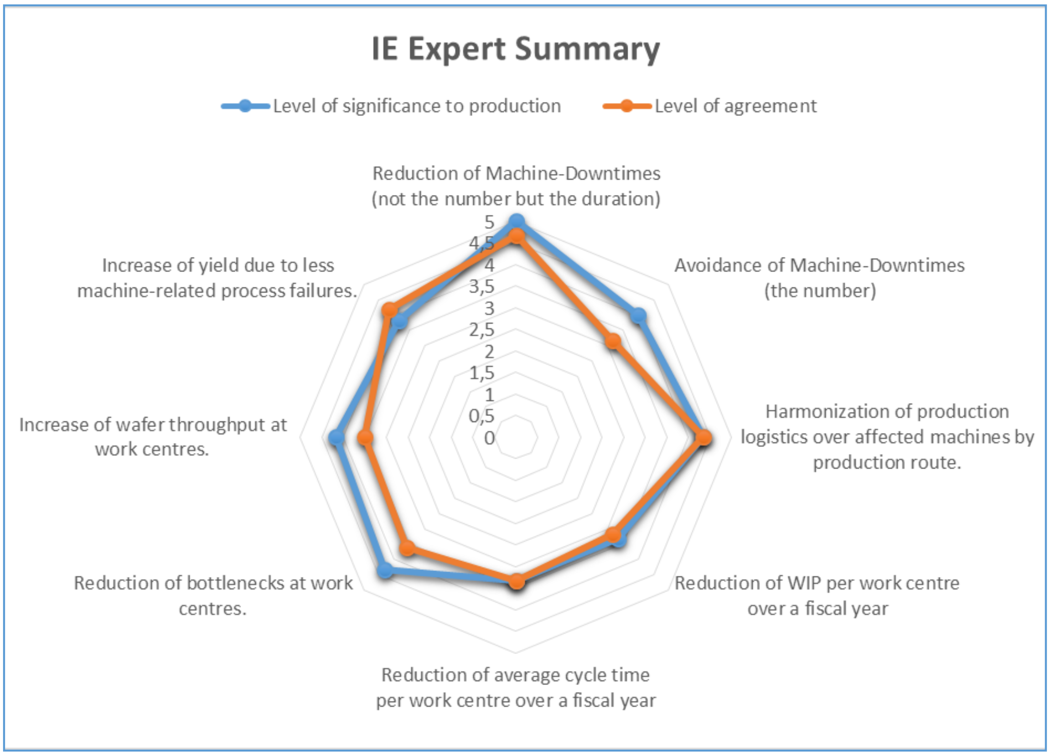


Figure 6-1: IE Expert Summary on PdM Expectations

Table 6-19 shows the KPIs or factors that were seen as impacted by the suggested effects triggered by a PdM application. Moreover, it contains the mean and standard deviation of the intensity of these effects. Each expectation may affect multiple KPIs or factors or none; thus, the experts were allowed to respond with ‘0’ to many questions. The terms were partially translated into English first, and then harmonised into common terms from the previously developed association matrix. When terms were named together without the intensity being differentiated, there were cases where the sign was not logically correct. A typical example was CT and GR, which ran synchronously to the mathematics from Little’s law. However, the signs were different in consideration of the same effect: a positive effect for GR meant ‘+’, whereas it meant ‘–‘ to CT. These cases were resolved directly before calculating the mean values of each effect.

Table 6-19: IE Expert Expectations on PdM

#	Expectation	Impacted KPIs or factors	Number of responses for effect	Intensity (mean)
1.	Reduction of Machine Downtimes (not the number but duration)	Alpha Tool	2	−9
		CT	2	−9
		FF	2	−8.5
		GR	3	8.33
		Equipment Availability	1	8
		MTOL	1	10
2.	Avoidance of Machine Downtimes (number)	Alpha Tool	2	−9
		CT	2	−7.5
		FF	2	−5
		GR	2	6
		Equipment Availability	1	8
		MTOL	1	10
3.	Harmonisation of production logistics over affected machines by production route	Alpha Tool	2	−10
		CT	2	−8.5
		FF	2	−7.5
		GR	2	6
		Equipment Availability	1	10
		Alpha WIP	2	−10
4.	Reduction of WIP per work centre over a fiscal year	Alpha PS	0	−9
		FF	2	−8.5
		CT	2	−5.5
		WIP	1	−7
		Little's law	1	N/A
5.	Reduction of average cycle time per work centre over a fiscal year	Alpha PS	1	−10
		FF	2	−8
		CT	3	−6.67
		Little’s law	1	N/A
6.	Reduction of bottlenecks at work centres	Alpha WIP	1	−8
		FF	1	−7
		CT	2	−9.5
		GR	1	9
7.	Increase in wafer throughput at work centres	Alpha PS	2	−8.5
		CT	1	−8
		GR	2	7.5
		WIP	1	−2
		WSPW	1	8
		Equipment Availability	1	8
		Little’s law	1	N/A
8.	Increase in yield because of fewer machine-related process failures	Percentage of Rework	1	−6
		Yield	2	6
		Scrap	1	−5
		CT	1	−4
		GR	1	4

Table 6-20 shows the mean and standard deviation of the EM expert responses to how much they agreed with the expectations.

Table 6-20: Results of EM Expectations on PdM (level of agreement)

#	Expectation	Level of agreement (mean)	Level of agreement (standard deviation)
1.	Increased coordination of maintenance processes	4.40	0.80
2.	More efficient spare part logistics	3.20	1.17
3.	Reduction of repair time	3.20	0.98
4.	Reduction of Machine Downtimes because of maintenance (not the number but duration)	4.50	0.87
5.	Avoidance of Machine Downtimes (number)	2.00	0.89
6.	Machine parts will be used nearly until end of their life cycle though application of preventive maintenance	4.20	0.75
7.	Increase in yield because of fewer machine-related process failures	4.20	1.17

Table 6-21 shows the mean and standard deviation of the EM expert responses to how significant the expectations are to production.

Table 6-21: Results of EM Expectations on PdM (level of significance to Production)

#	Expectation	Level of significance to production (mean)	Level of significance to production (standard deviation)
1.	Increased coordination of maintenance processes	4.20	0.75
2.	More efficient spare part logistics	2.80	0.98
3.	Reduction of repair time	3.80	0.75
4.	Reduction of Machine Downtimes due to maintenance (not the number but duration)	4.75	0.43
5.	Avoidance of Machine Downtimes (number)	3.60	1.50
6.	Machine parts will be used nearly until end of their life cycle though application of preventive maintenance	3.80	0.40
7.	Increase in yield because of fewer machine-related process failures.	4.20	1.17

Figure 6-2 presents a comparison between the EM experts' agreement with and opinions regarding the suggested expectations' significance to production. Although the effects from single expectations would have a significant impact on PS performance, not all of them could be achieved through applying PdM. An obvious difference was found for expectation #5 ('Avoidance of Machine Downtimes'), which the experts tended to assign a medium to high significance to production, without believing that PdM would support such an improvement. The biggest positive overlap in levels of agreement as well as level of significance to production was found for the increased coordination of EM processes, reduction of machine downtime durations, and the exhausting of machine component wear limits. The experts saw PdM as an effective tool for improvement for these aspects.

Table 6-22 shows the KPIs or factors that were seen as being impacted by the suggested effects that were triggered by a PdM application. Furthermore, it contains the mean and standard deviation of the intensity of the effects. Data cleansing was performed in the same manner as described in the IE part of the thesis.

Table 6-22: EM Expert Expectations on PdM

#	Expectation	Impacted KPIs or factors	Number of responses for effect	Intensity (mean)
1.	Increased coordination of maintenance processes	FF	2	−5
		MTBF	1	5
		MTOL	1	−7
		QE	1	7
		Equipment Availability	2	8
		EM costs	2	−5.5
		MTTR	3	−6.67
		Personnel costs	1	−8
2.	More efficient spare part logistics	EM costs	2	−6
		Inventory costs	1	−4
		Spare part costs	1	−5
		Equipment Availability	3	7
		MTTR	1	−8
3.	Reduction of repair time	FF	1	−10
		MTOL	2	7.5
		Equipment Availability	2	5.5
		MTTR	4	−5.25
4.	Reduction of Machine Downtimes due to maintenance (not the number but duration)	Equipment Availability	2	6
		MTOL	3	−9
		MTTR	1	−4
		OEE	1	10
		MTBF	1	10
5.	Avoidance of Machine Downtimes (number)	Equipment Availability	2	5.5
		FF	1	−5
		MTBF	2	7
		MTOL	2	−7
		MTTR	1	−5
		OEE	1	5
6.	Machine parts will be used nearly until end of their life cycle though application of preventive maintenance	EM costs	3	−7
		Equipment Availability	2	7.5
		MTBF	1	5
		Spare part costs	2	−7.5
7.	Increase in yield because of fewer machine-related process failures	Product costs	1	−10
		Yield	6	8.67

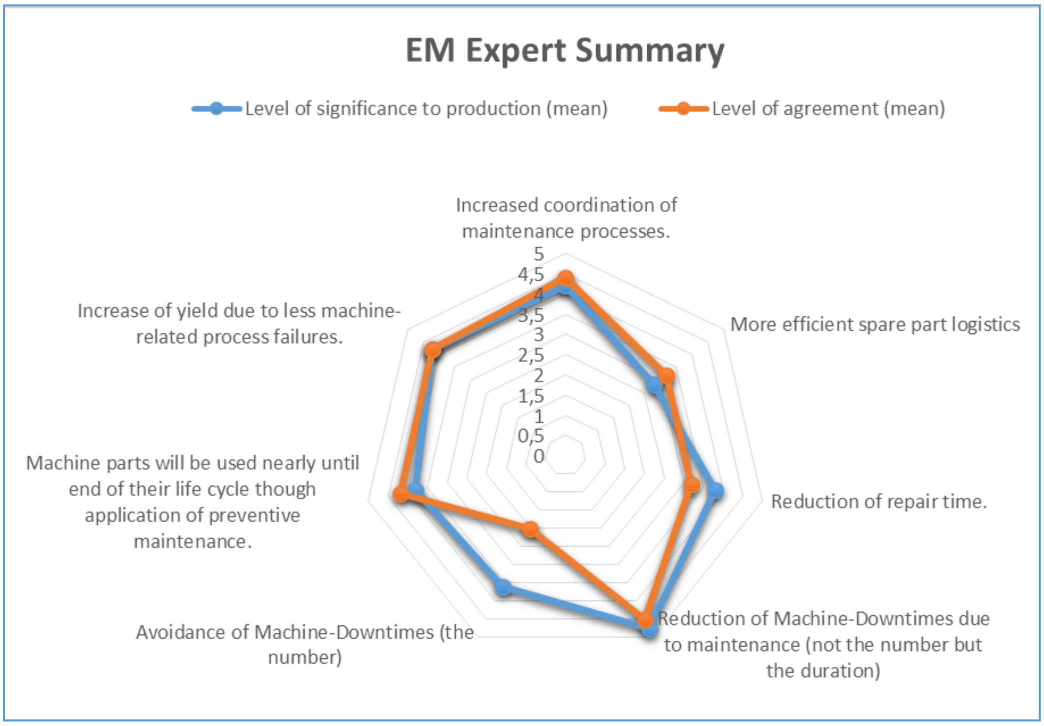


Figure 6-2: EM Expert Summary on PdM Expectations

6.5 Consolidation and Evaluation

This section consolidates the individual analysis results to support an overall data evaluation. The goal of this section is to create a comprehensive CLM that stores the identified influences between SI PS elements mutually and influences of PdM on these elements. This model will act as an existential basis for the PPES development as well as for the PdMSM development. First, the identified terms from both the IE and EM have to be harmonised to concatenate them. The following aspects should be considered:

1. Different naming conventions (e.g., ‘variance of xy’ vs. ‘xy variance’)
2. Usage of abbreviations (e.g., ‘EM’ vs. ‘maintenance’)
3. Missing or different transformations (e.g., ‘xy’ vs. ‘Importance of xy’)
4. Different text style for upper and lower case (all terms were harmonised to camel case)

Because the fourth aspect affects nearly all terms and the resolution procedure is trivial, it will not be discussed in details. Table 6-23 lists the required transformations from rules 1 to 3 to achieve a harmonised set of terms between the IE and EM data.

Table 6-23: Term Transformation for IE and EM harmonised Data

#	Original	Transformed To
1	Capacity	Equipment Capacity
2	Dispatcher Compliance	Degree Of Dispatcher Compliance
3	Downtime Frequency	Equipment Downtime Frequency
4	Duration Of Machine Downtimes	Equipment Downtime Duration
5	Equipment Going Rate	Equipment GR
6	Evenness Of Distribution Of Equipment Downtimes	Degree Of Evenness Of Distribution Of Equipment Downtimes
7	Frequency Of Unscheduled Machine Downtimes	Unscheduled Down Frequency
8	High Percentage Process Inspections	Percentage Of Process Inspections
9	Maintenance Strategy	Maturity Of EM Strategy
10	Performance Synchronicity Of Similar Machines	Degree Of Performance Synchronicity Between Similar Machines
11	Probability To Avoid Machine-Downtimes	Probability To Avoid Machine Downtimes
12	Process Development At Production Equipment	Percentage Of Process Development At Production Equipment
13	Rework	Percentage Of Rework
14	Tool Dedication	Degree Of Tool Dedication

Partially, the mathematical associations between factors and KPIs shown in Chapter 4 were also stated by the experts. However, not all of them are contained in the current data matrix. Because the PPES is intended to include all known associations to provide a full picture of the SI PS performance, the mathematical associations from the literature must be added in this section. Only trivial dependencies such as the overall time the factory exists or the overall number of items that have been fabricated are skipped for the further model development. It is not necessary to specify a certain impact value because the mathematical dependencies are well defined. Table 6-24 shows the mathematical associations that is added to the data matrix.

To add the associations from the rated expectations on how PdM influences PS indicators, the given expectations have to be transformed into quantifiable but neutral terms. This transformation is primarily for searching the terms already named by the experts to foster concatenated effects. The source was constantly set as ‘PdM Application’ because it is the influencing part of this association. The impact was calculated based on the level of agreement by the experts with that particular expectation because it describes the quantified impact of PdM on each expectation.

Table 6-24: Mathematical Associations for PPES

#	Source	Type	Target
1	Equipment Capacity	decrease	Equipment Utilisation
2	GR	increase	Equipment Utilisation
3	Equipment GR	increase	Equipment Capacity
4	Equipment Availability	increase	Equipment Capacity
5	Process Availability	increase	Equipment Capacity
6	Raw Process Time	decrease	Alpha Tool
7	Equipment Availability	decrease	Alpha Tool
8	MTOL	increase	Alpha Tool
9	Raw Process Time	decrease	FF
10	CT	increase	FF
11	GR	decrease	CT
12	WIP	increase	CT
13	Wait Time	increase	CT
14	Fabricated Items Per Time	increase	GR
15	Equipment Availability	increase	DGR
16	Process Availability	increase	DGR
17	Fabricated Items Per Day	increase	DGR
18	Operator Availability	increase	DGR
19	WIP Availability	increase	DGR
20	Equipment Availability	increase	PS Availability
21	Process Availability	increase	PS Availability
22	Fabricated Items Per Day	increase	PS Availability
23	Operator Availability	increase	PS Availability
24	WIP Availability	increase	PS Availability
25	OE	increase	OEE
26	QE	increase	OEE
27	RE	increase	OEE
28	Equipment Availability	increase	OEE
29	Number Of Wafers To Rework	decrease	QE
30	Number Of Wafers To Scrap	decrease	QE
31	Number Of Assists	decrease	MTBA
32	Number Of Failures	decrease	MTOL
33	Number Of Failures	decrease	MTBF
34	Number Of Failures	decrease	MTTF
35	Number Of Failures	decrease	MTTR

Because of the different numbers of dimensions (0–5 vs. 0–10), the impact value has to be multiplied by 2 to add the equivalent significance, as with the other associations. Table 6-25 shows the transformation for the EM part.

Table 6-25: Transformed EM Expectations on PdM into Terms

#	Source	Expectation	Target (transformed)	Impact (Level of agreement [mean]*2)
1	PdM Application	Increased coordination of maintenance processes	Efficiency In Coordination Of Maintenance Process	8.8
2	PdM Application	More efficient spare part logistics	Efficiency Of Spare Part Logistics	6.4
3	PdM Application	Reduction of repair time	Repair Time	−6.4
4	PdM Application	Reduction of Machine Downtimes because of maintenance (not the number but duration)	Equipment Downtime Duration	−9
5	PdM Application	Avoidance of Machine Downtimes (number)	Probability To Avoid Machine Downtimes	4
6	PdM Application	Machine parts will be used nearly until end of their life cycle though application of preventive maintenance	Degree Of Exhausting Wear Limits	−8.4
7	PdM Application	Increase in yield because of fewer machine-related process failures	Degree Of Machine-Related Process Failures	8.4

The same procedure is applied for the IE expectations on PdM. Table 6-26 shows the transformation for the IE part.

Table 6-26: Transformed IE Expectations on PdM into Terms

#	Source	Expectation	Target (transformed)	Impact (Level of agreement [mean]*2)
1	PdM Application	Reduction of Machine Downtimes (not the number but duration)	Equipment Downtime Duration	−9.34
2	PdM Application	Avoidance of Machine Downtimes (number)	Probability To Avoid Machine Downtimes	6.34
3	PdM Application	Harmonisation of production logistics over affected machines by production route	Material Flow Variance	−8.66
4	PdM Application	Reduction of WIP per work centre over a fiscal year	WIP	−6.34
5	PdM Application	Reduction of average cycle time per work centre over a fiscal year	CT	−6.66
6	PdM Application	Reduction of bottlenecks at work centres	Percentage Of Bottleneck Equipment	−7.2
7	PdM Application	Increase in wafer throughput at work centres	GR	7
8	PdM Application	Increase in yield because of fewer machine-related process failures	Degree Of Machine-Related Process Failures	−8.34

After processing the harmonisation of terms, the IE and EM associations were merged into a common data matrix enriched by the mathematical associations and transformed PdM expectations. Subsequently, the consolidated data has to be analysed against redundancies and inconsistencies (decrease vs. increase) between EM and IE experts. Only two inconsistencies were found in the associations between the following terms:

1) 'Probability To Avoid Machine Downtimes' on 'MTOL'
   a. This inconsistency can be resolved using 'decrease' following the majority of responses.
2) 'Equipment Downtime Duration' on 'MTOL'
   a. This inconsistency can be resolved using 'increase' following the majority of responses.

The redundant associations should be processed to be unique and require a harmonised impact value in order to generate clear logical rules and a consistent simulation model. To consider the number of experts behind the given impact value, the resolution procedure applied a weighted average of impacts using the numbers of responses from each association.

Table 6-27 shows the redundant associations and the recalculated impact values.

Table 6-27: Resolved Redundancies with Recalculated Impact Values

#	Source	Type	Target	Impact (weighted average)
1	Equipment Downtime Duration	decrease	Equipment Availability	−6.67
2	Equipment Downtime Duration	increase	MTOL	9.25
3	Percentage Of Bottleneck Equipment	increase	CT	9.00
4	PdM Application	decrease	Degree Of Machine-Related Process Failures	−8.37
5	PdM Application	decrease	Equipment Downtime Duration	−9.19
6	PdM Application	increase	GR	6.55
7	PdM Application	increase	Probability To Avoid Machine Downtimes	5.28
8	Probability To Avoid Machine Downtimes	increase	Equipment Availability	6.33
9	Probability To Avoid Machine Downtimes	decrease	FF	−5
10	Probability To Avoid Machine Downtimes	decrease	MTOL	−8
11	Degree Of Machine-Related Process Failures	decrease	Yield	−8

At this stage, the overall data matrix is finished. It will serve as the primary basis for developing PPES and PdMSM. The matrix consists of all identified associations relevant to this study. Figure 6-4 shows the overall CLM that is created from the data matrix. The figure is divided into four parts P1 to P4 that are shown in more detail in the following Figures 6-4 to 6-7. The arrows indicate associations from a source term to a target term where a target term is connected to the arrowhead. Each arrow is marked with a sign: The minus sign (‘–‘) refers to decreasing influences, whereas the plus sign (‘+’) refers to increasing influences.

Overall, the CLM consists of 134 harmonised terms, which are part of 272 logical associations. However, the terms can be rated by their importance because their application within associations is spread widely. Figure 6-3 shows this distribution.

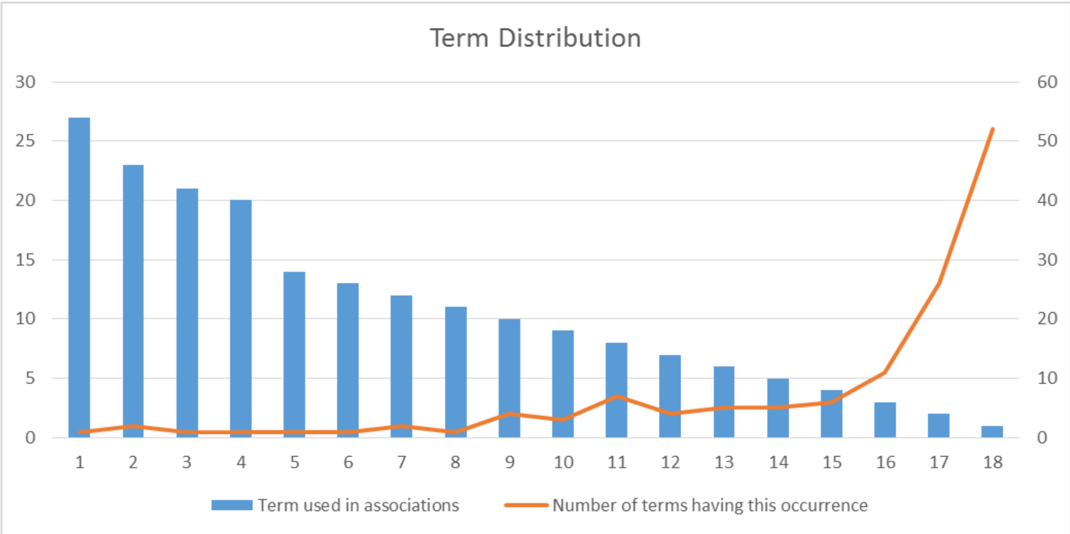


Figure 6-3: Distribution of Term Usage in Associations

The blue bars visualise the number of occurrences of a term in associations (scale on the left side), whereas the orange line shows the number of terms that match this occurrence (scale on the right side). Both numbers consider only the harmonised overall results and not the sum of occurrences within all interviews.

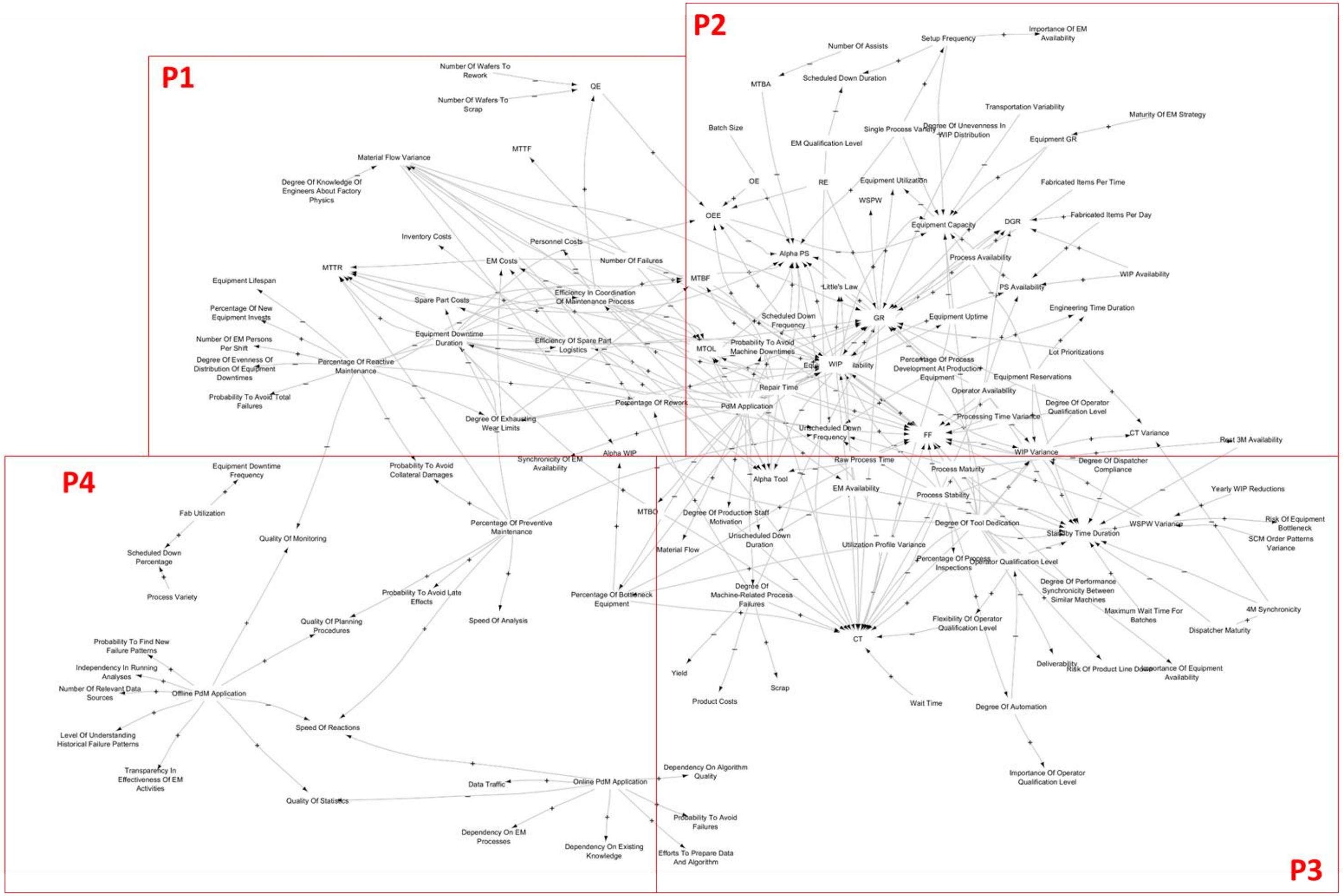


Figure 6-4: Overall CLM

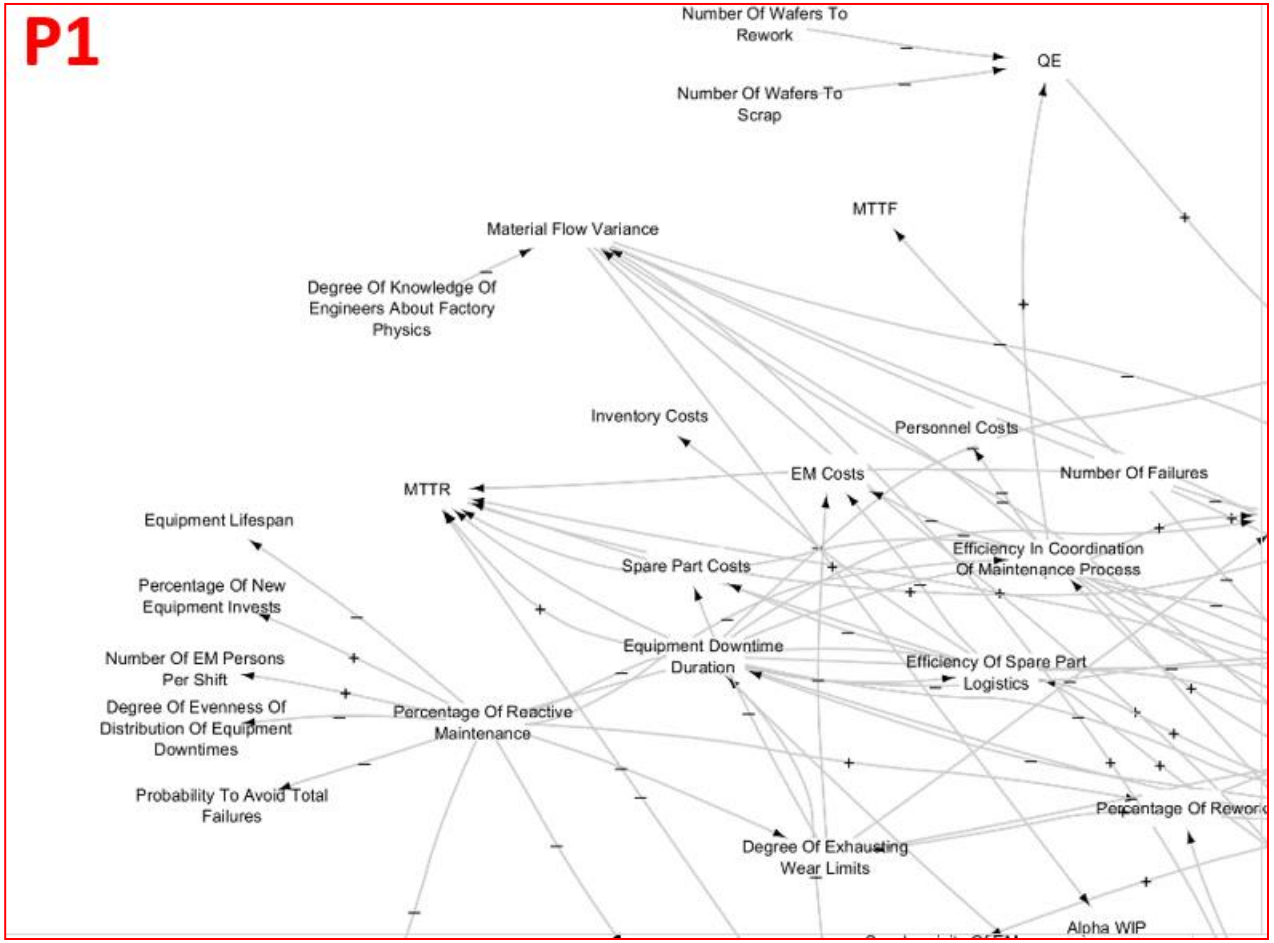


Figure 6-5: P1 Part of the CLM

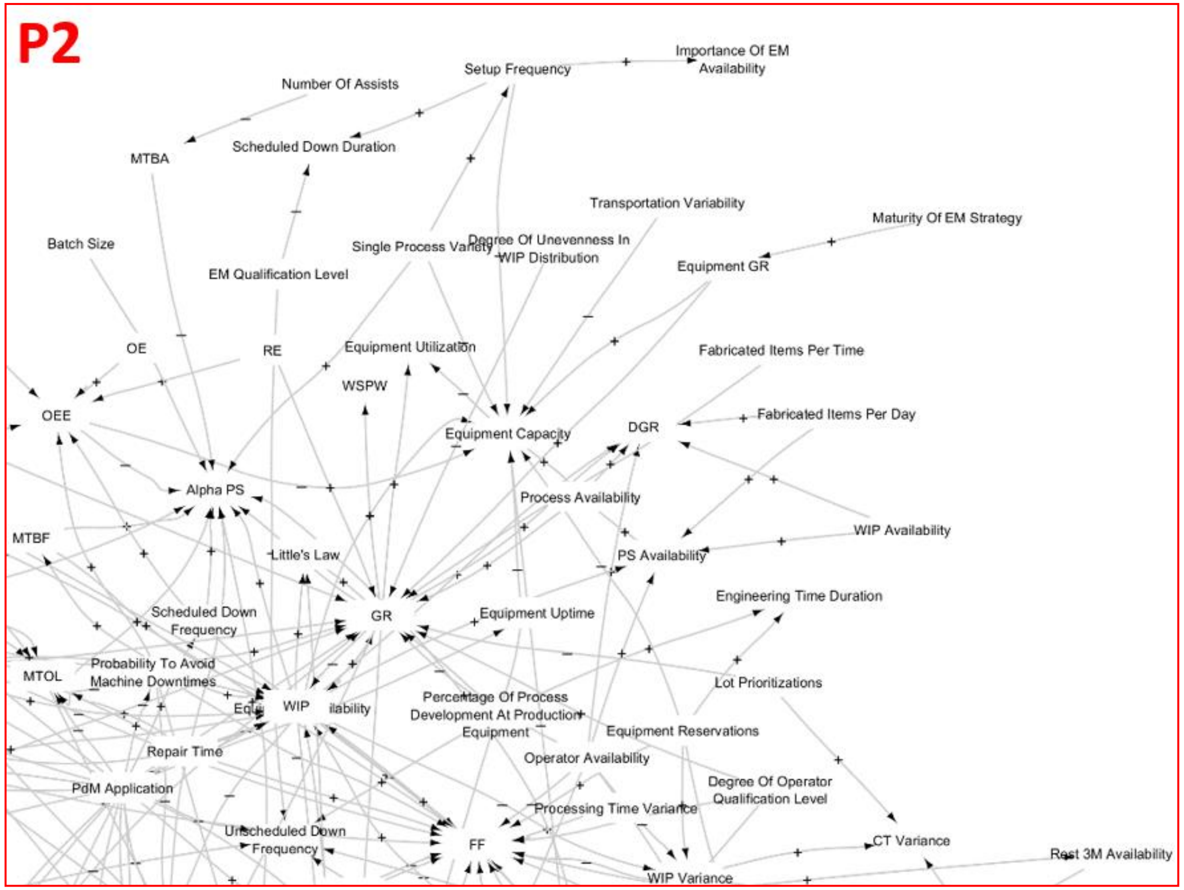


Figure 6-6: P2 Part of the CLM

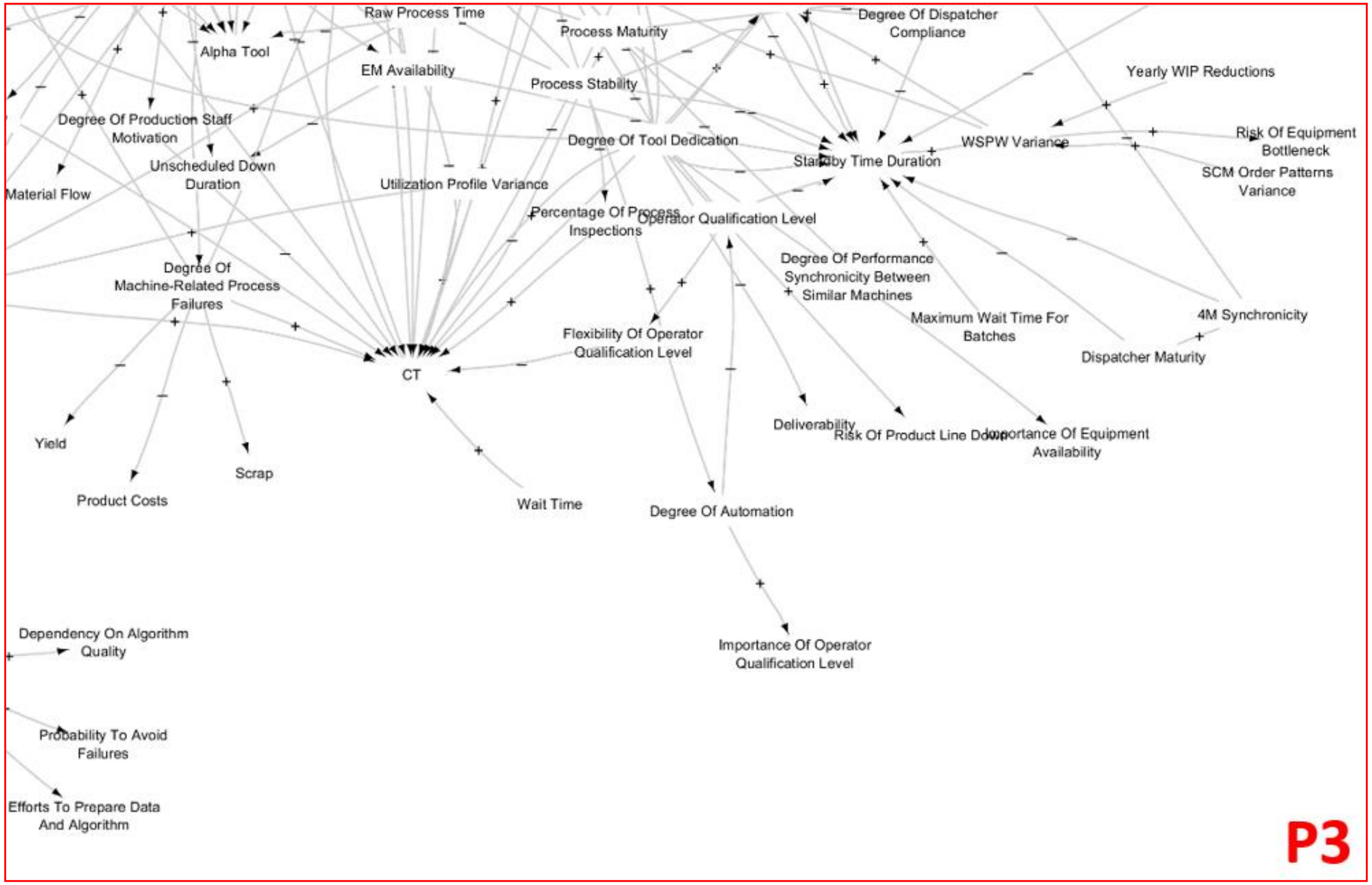


Figure 6-7: P3 Part of the CLM

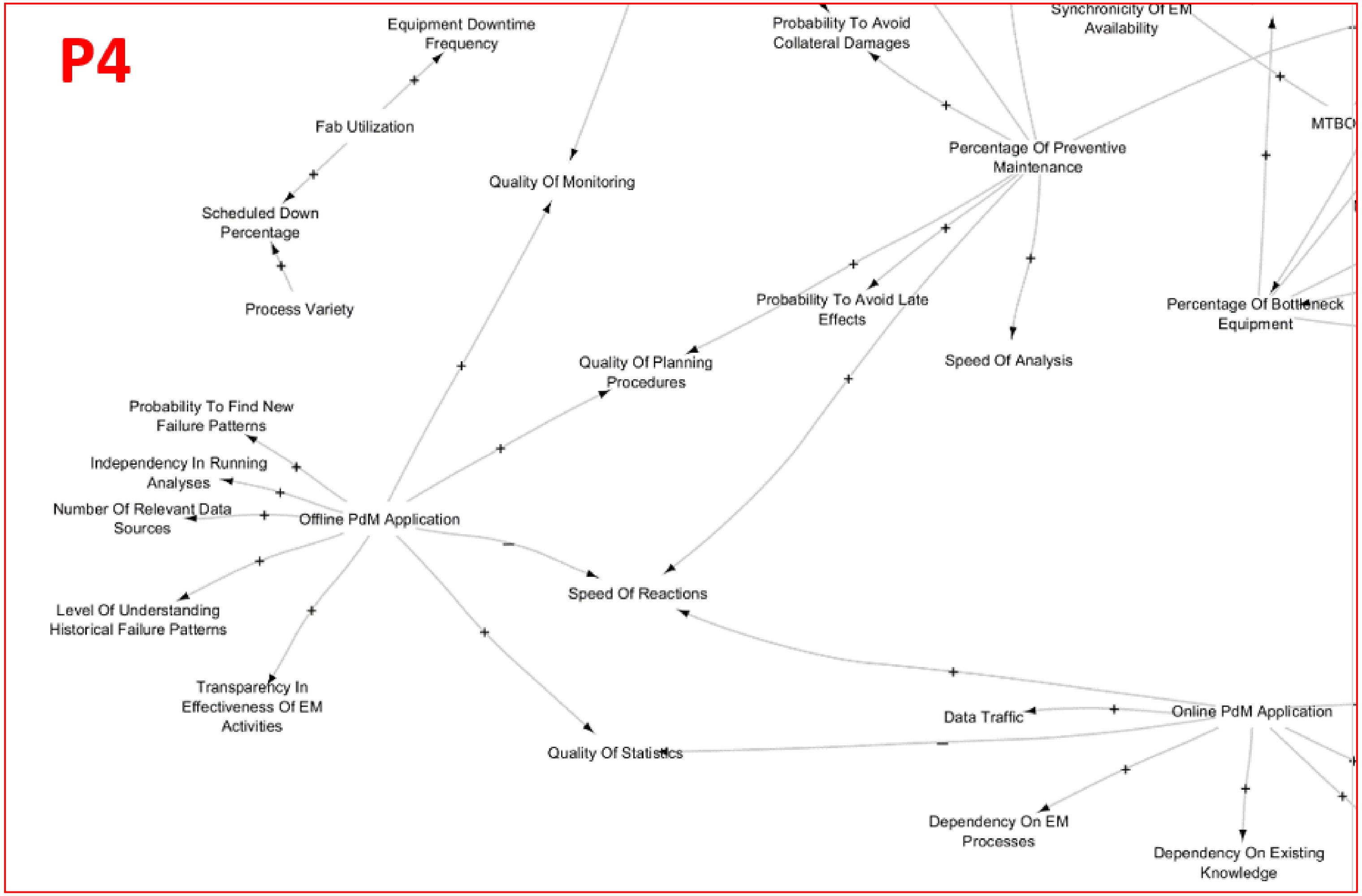


Figure 6-8: P4 Part of the CLM

This study suggests that the number of occurrences is an indicator of the importance of a specific term in this research context. This is justified by the fact that those terms either significantly influence other terms or are significantly impacted by other terms directly. Although the ranking is not intended to imply a general importance in terms of PS performance management, the terms are potentially the most critical factors and indicators when analysing the impact of PdM as a specific PA application on the PS performance in SI. This identified importance is used for the development of the simulation model for RO 4 to differentiate the weight of effects. The chart shows that only a few terms were used in many associations and a large number of terms were only used once. Table 6-28 shows the 21 most important terms that were included in 50% of all associations.

Table 6-28: Most important Terms rated by Occurrence in Associations

#	Terms	Occurrence	Percentage	Accumulation
1	GR	27	4.97%	4.97%
2	CT	23	4.24%	9.21%
3	PdM Application	23	4.24%	13.44%
4	FF	21	3.87%	17.31%
5	Equipment Availability	20	3.68%	20.99%
6	Standby Time Duration	14	2.58%	23.57%
7	Alpha PS	13	2.39%	25.97%
8	Equipment Downtime Duration	12	2.21%	28.18%
9	Percentage Of Reactive Maintenance	12	2.21%	30.39%
10	Equipment Capacity	11	2.03%	32.41%
11	Degree Of Tool Dedication	10	1.84%	34.25%
12	Efficiency In Coordination Of Maintenance Process	10	1.84%	36.10%
13	Probability To Avoid Machine Downtimes	10	1.84%	37.94%
14	WIP Variance	10	1.84%	39.78%
15	Material Flow Variance	9	1.66%	41.44%
16	Offline PdM Application	9	1.66%	43.09%
17	Process Stability	9	1.66%	44.75%
18	Alpha Tool	8	1.47%	46.22%
19	MTOL	8	1.47%	47.70%
20	MTTR	8	1.47%	49.17%
21	OEE	8	1.47%	50.64%

Another indicator for rating the importance of terms is the number and degree of impact on other terms. This helps to differentiate the terms as candidates for influencing parameters from terms that are instead candidates for KPIs. The source terms were evaluated by their occurrence in associations in order to generate an importance profile. Figure 6-9 presents the results from this evaluation for the influencing terms.

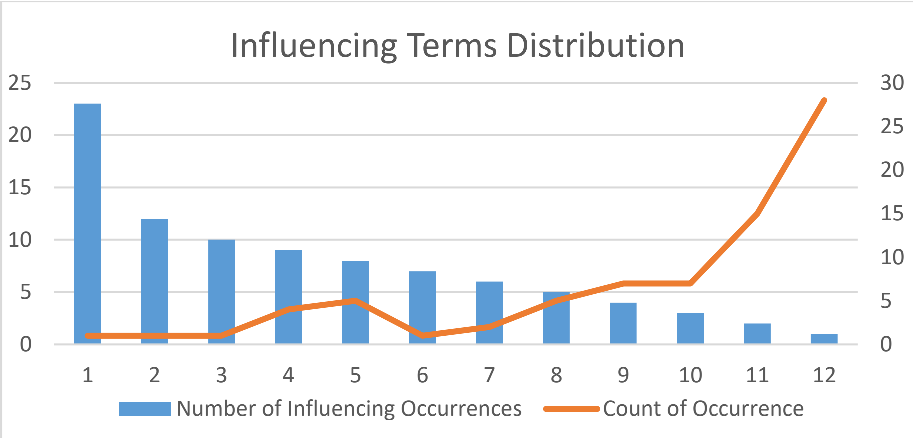


Figure 6-9: Distribution of Influencing Terms

The blue bars visualise the number of occurrences of an influencing source term in associations (scale on the left side), whereas the orange line shows the number of terms that match this occurrence (scale on the right side). The result is similar to the overall distribution, showing that a few source terms have a high number of occurrences in all associations. The analysis reveals that 21% of all source terms are the influencing factors within 50% of all associations, and 56% only have an impact on one or two terms. Table 6-29 lists the most influential source terms that have an impact on 50% of all identified associations.

Table 6-29: Most Influential Source Terms

#	Source Term	Occurrences	Percentage	Accumulation
1	PdM Application	23	8.46%	8.46%
2	Percentage Of Reactive Maintenance	12	4.41%	12.87%
3	Degree Of Tool Dedication	10	3.68%	16.54%
4	Equipment Downtime Duration	9	3.31%	19.85%
5	GR	9	3.31%	23.16%
6	Offline PdM Application	9	3.31%	26.47%
7	Probability To Avoid Machine Downtimes	9	3.31%	29.78%
8	Efficiency In Coordination Of Maintenance Process	8	2.94%	32.72%
9	Equipment Availability	8	2.94%	35.66%
10	Online PdM Application	8	2.94%	38.60%
11	Percentage Of Preventive Maintenance	8	2.94%	41.54%
12	Process Stability	8	2.94%	44.49%
13	Operator Availability	7	2.57%	47.06%
14	Degree Of Machine-Related Process Failures	6	2.21%	49.26%
15	Material Flow Variance	6	2.21%	51.47%

By contrast, Figure 6-10 shows the distribution of influenced terms to their occurrence in associations. Similarly, the blue bars visualise the number of occurrences of an influenced target term in associations (scale on the left side), whereas the orange line shows the number of terms that match this occurrence (scale on the right side). The distribution tends even more toward unevenness compared with the influenced terms and shows that a smaller number of terms were impacted by many associations, whereas a larger number of terms were only impacted rarely. The calculation shows that 13% of all target terms were impacted by 50% of all associations, and 74% of all target terms were impacted only once or twice. Similarly, the blue bars visualise the number of occurrences of an influenced target term in associations (scale on the left side), whereas the orange line shows the number of terms that match this occurrence (scale on the right side). The distribution tends even more toward unevenness compared with the influenced terms and shows that a smaller number of terms were impacted by many associations, whereas a larger number of terms were only impacted rarely. The calculation shows that 13% of all target terms were impacted by 50% of all associations, and 74% of all target terms were impacted only once or twice.

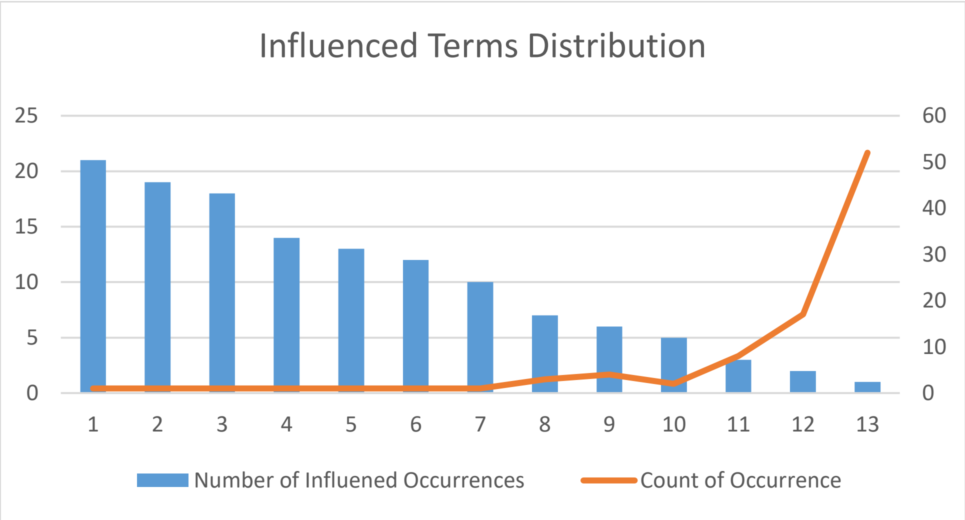


Figure 6-10: Distribution of Influenced Terms

Table 6-30 lists the 12 most influenced target terms that were impacted by 50% of all identified associations.

Table 6-30: Most Influenced Target Terms

#	Target Term	Occurrences	Percentage	Accumulation
1	FF	21	7.72%	7.72%
2	CT	19	6.99%	14.71%
3	GR	18	6.62%	21.32%
4	Standby Time Duration	14	5.15%	26.47%
5	Alpha PS	13	4.78%	31.25%
6	Equipment Availability	12	4.41%	35.66%
7	Equipment Capacity	10	3.68%	39.34%
8	Alpha Tool	7	2.57%	41.91%
9	MTTR	7	2.57%	44.49%
10	WIP Variance	7	2.57%	47.06%
11	DGR	6	2.21%	49.26%
12	MTOL	6	2.21%	51.47%

With these two lists of evaluated terms, this study found the most relevant PS characteristics that are either influencing or influenced when applying PdM as a concrete PA application on SI PS. For instance, it can be expected from the evaluation that PdM in SI PS would not significantly influence the ‘Probability To Avoid Machine Downtimes’, whereas this characteristic itself would be a critical driver for PS performance improvement. By contrast, the GR is a PS characteristic that would be impacted significantly by PdM applications, and would also influence numerous other PS performance factors.

6.6 Summary

This chapter presented the analysis of the expert interview data and the development and evaluation of a CLM. This model states that the causal relationships between the application of PdM and its influences on the performance-critical characteristics of an SI PS can be identified. Prior to the overall CLM, two sub-models were developed independently. The sub-model from the IE perspective is concentrated on the causal relationships between elements and factors within the SI PS, whereas the sub-model from the EM perspective focusses on the causal relationships between maintenance strategies and machine-oriented performance indicators. The overall CLM combines both sub-models and consists of records that indicate which source term has an increasing or decreasing impact on a target term including the weight of the impact. This information is the basis for the advanced analysis methods that are developed and evaluated in Chapter 7 and Chapter 8.

The direct benefits that PdM might facilitate have been pointed out, such as the reduction of machine downtimes or the increased coordination of maintenance processes. However, according to the IE and EM experts, PdM would not directly help to avoid machine downtimes. Based on the number of occurrences in impact associations, the most directly influenced terms as well as the most directly influencing terms were discovered. Although the IE experts did not believe that PdM would directly affect the PS performance, the causal loop relationships revealed high occurrences of FF, CT, and GR as target terms within all captured associations. However, the advanced analysis capabilities of PPES and PdMSM are required to reveal the transitive impacts of PdM on those indicators.

Chapter 7 A Production Performance Expert System for the SI

7.1 Introduction

The data analysis in Chapter 6 results in the CLM that establishes the relationships between the essential terms from SI PS and PdM. However, the data is not yet in the format that is required by software-based analysis procedures to generate transitive knowledge. The reason for this is that the majority of terms is a combination of single words, for instance ‘Importance Of EM Availability’. Whereas a human reader with the necessary expertise is able to split the term into useful atomic parts, a knowledge-based system requires additional descriptive characteristics. This chapter will discuss the transformation of these terms and associations into a knowledge-based system called PPES. The CLM represents the so-called ‘word model’ as a major prerequisite, which describes the model logic in a textual way. As discussed in 3.2.3, the CLM consists of a set of data on causes and effects in the system structure and a set of characteristic parameters of individual processes within the system.

Though the data of time series is not required to create the model, the data is important for model validation. The required data has been identified during the case study and extracted from the IT systems. This data is used in a later stage of the project to prove the correctness simulation model.

Stanford University researchers Noy and McGuinness (2000) published a methodology to develop ontologies using the software Protégé. According to Google Scholar, more than 5,700 publications cited this particular methodology. Due to its acceptance in science, it acts as inspiration for the PPES development procedure. The procedure consists of the following sequential steps:

1) Define the scope and boundaries of the ontology.
2) Transform the identified terms from the case study into ontology concepts.
3) Create the class hierarchy and entity specifications.
4) Define and develop the required object properties.

5) Define and develop the FOL rules to model the direct effect associations and to enable logical inference to derive additional knowledge.

To prove the PPES logic is correct, and to extract new knowledge, the ontology and its inference engine require so-called ‘individuals’. These objects are specific instances of the concepts that are part of the class hierarchy. Finally, the new transitive knowledge regarding impacts of PdM on SI PS performance is presented. The results of the PPES have been used to further develop the simulation model.

7.2 Scope and Boundaries

To define the scope and boundaries of PPES as an ontology, Noy and McGuiness (2000) suggested asking the following questions:

1) What domain will the ontology cover?
2) For what are we going to use the ontology?
3) For what types of questions should the information in the ontology provide answers?
4) Who will use and maintain the ontology?

These questions are crucial to generate an unambiguous language within the ontology, especially for terms that have another meaning in different contexts. The high quality of the language is the foundation for the correct application of logical inference. Table 7-1 defines the characteristics that specify the PPES scope and boundaries.

Table 7-1: PPES Scope and Boundaries

Characteristic	**Value**
Ontology domain	SI PS
Ontology purpose	Analysis of impacts of PdM on SI PS performances
Types of questions to be answered	• What are the critical characteristics of SI PS elements that influence the SI PS performance? • How are SI PS elements and characteristics connected, logically? • How does PdM directly affect SI PS performance? • Which transitive impacts of PdM on SI PS performance exist beyond the ones mentioned by the interviewees? • Which contradictory impacts exist that interviewees did not mention?
Ontology user group	Business Analysts, Industrial Engineers, EM Engineers, Academic Researchers

7.3 Term Transformation into Ontology Concepts

This section presents the process of concept generation based on the case study results. The identified terms in the data matrix have been transformed into quantifiable variables. This procedure requires a separation of multiple aspects from the core variable to gain unique elements. Only with unique elements is it possible to generate knowledge within the given term relationships. Otherwise, terms that refer to the same core element would not be logically connected. Ressler et al. (2007) described a software-based transformation and propose a separation by following types of data within an ontology:

- Individual variables (in Protégé known as classes or concepts)
- Data-valued variables (in Protégé known as data properties)
- Literal variables (in Protégé known as individuals)
- Relationships (can be either object properties or class hierarchies in Protégé)
- Built-in operators and functions

All types of properties and classes are called 'entities' in Protégé. This project uses the naming conventions from Protégé within the thesis in terms of ontology generation. In contrast to an object-oriented class model, the single variables are associated rather loosely. In object-oriented class models, a certain attribute is only defined and valid within a certain class. However, in ontologies, an attribute is principally defined in a public way and can be shared by multiple classes. Figure 7-1 shows the principal data model conventions in ontology according to Ressler et al. (2007).

There is always one generic root class for all subclasses that is named 'Thing' by default. Protégé does not allow the creation of parallel classes at root level. Classes can have a hierarchical relationship including the inheritance of class definitions or relationships. A class hierarchy does not have to be balanced, thus, each branch may consist of individual levels and a number of sub-classes. Fortunately, there exists best practice advice from literature on how to evaluate the quality of class hierarchies, which is summarised below (Noy and McGuinness, 2000):

1) If a class only consists of one direct subclass, there may be a modelling problem or the ontology is not complete.
2) If there are more than a dozen subclasses for a given class, additional intermediate categories may be necessary.

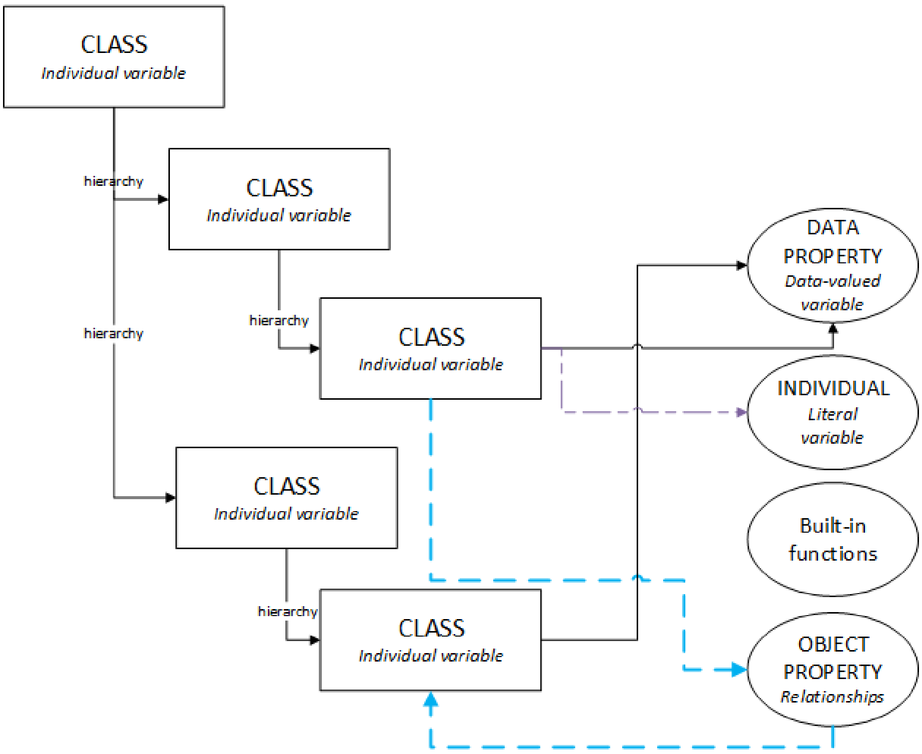


Figure 7-1: Ontology Data Model Conventions inspired by Ressler et al. (2007)

All kinds of properties are defined individually and do not belong to any class by default. Thus, different classes can use the same property. The actual usage needs to be defined either by class or by property since the software allows both perspectives. Where data properties are used to store any kind of value, object properties are used to specify logical relationships between classes. Individuals can be instances of classes, but can also be independent to represent anything specific. Built-in functions are provided by the software and can be used to do mathematical operations or logical comparisons such as ‘is greater than’.

The transformation procedure needs to run the following steps in sequence:

1. For each term:
    1.1. Extract terms, source/target information and relationship types from all associations.
    1.2. Split the terms into atomic elements as far as logically possible to create single concepts.
2. For each concept:
    2.1. Categorize the concept by ontology object type.
    2.2. Ensure a standardized format of concepts and transform concepts into singular if required and possible.
    2.3. Identify common classifiers as the basis for the tree hierarchy.
    2.4. Search for equivalent concepts and store this information.
    2.5. Search for opposite concepts and store this information.

Finally, a raw data model has been created from the transformed data to prove the correctness compared to the initial terms and relationships.

As an example, the transformation procedure has been applied on the following records from the data matrix as shown in Table 7-2.

Table 7-2: Sample Records from the Case Study Data Matrix

Source	**Type**	**Target**
WSPW Variance	increase	Risk of Equipment Bottleneck
Percentage Of Bottleneck Equipment	increase	Alpha WIP

First, the terms need to be extracted:

1) ‘WSPW Variance’
2) ‘Risk of Equipment Bottleneck’
3) ‘Percentage Of Bottleneck Equipment’
4) ‘Alpha WIP’
5) ‘Increase’

Then, the atomic elements of all terms must be identified. The most appropriate split of elements depends on the intended way of modelling the final ontology. Thus, it might happen that atomic elements need to be changed or merged when processing the algorithm. The procedure uses the ‘Maximum Matching Algorithm’, also known as ‘Greedy Algorithm’, to achieve a standardized word segmentation. The algorithm starts with the first character of a term, iterates through the string and concatenates the characters. Each iteration checks the existence of the currently concatenated characters against a valid dictionary. As soon as an existing word has been found, the algorithm continues searching for the next word within the term using the same iterative approach. When the algorithm has reached the end of a term string, it continues with the next term until all words from all terms have been segmented accordingly (Cohen and Wahlster, 1997). As an additional rule, all prepositions are removed so that only nouns, verbs, established terms and phrases whose words belong together for the ontology are considered. For the sample terms from above, the word segmentation leads to following results:

1) [WSPW] + [Variance]
2) [Risk] + [Equipment] + [Bottleneck]
3) [Percentage] +[Bottleneck] +[Equipment]
4) [Alpha] + [WIP]
5) [increase]

Next, the atomic elements have to be classified by their ontology component type. The most fundamental question is whether an element is a class or a property. This can only be decided using the ontology domain specification and real-world target. This means that the decision could be different in another domain having other kinds of processes, products or challenges. Noy and McGuiness (2000) proposed a few guidelines to decide for the proper classification. Generally, if a class with different property values becomes a restriction for different properties in other classes, then an element should be created as new class for the distinction. Otherwise, it can be represented as distinction through a property value. Another aspect is if the element would be treated as single real-world object in the ontology domain, then it should be created as class. Further, the class has to be stable enough so that its individuals do not have to change classes often. Another distinction needs to be made between a class and an individual. According to Noy and McGuiness (2000), individuals are the most specific concepts represented in the knowledge base. Thus, other individuals cannot inherit their characteristics. Another limitation in knowledge databases is that the hierarchy model cannot manage individuals. Thus, it can make sense to define terms as classes even if they do not have any instance of their own in cases where they represent a valuable element of the domain (Noy and McGuinness, 2000). Since the ontology as a knowledge base shall be able to manage all concepts equally, it is mostly required to define concepts as classes.

These guidelines lead to the following proposed classifications for the identified unique elements:

1) [Variance]: Class
2) [WSPW]: Class
3) [Risk]: Class
4) [Bottleneck]: Class
5) [Equipment]: Class
6) [Percentage]: Class
7) [Alpha]: Class
8) [WIP]: Class
9) [Increase]: Object Property

Depending on the actual usage of the ontology, it may be required to specify the concepts in more details. Such details could be attached via data properties to provide a basis for mathematical calculations. Since this ontology is not intended to perform such value-based calculations, a high-level representation of real objects as classes is considered sufficient. The concepts ‘Percentage’ and ‘Risk’ are treated as equal to keep the example simple for demonstration reasons. The term ‘increase’ represents a pure relationship between two classes, and therefore, can be classified as object property. Depending on the ontology usage, it could be modelled as class as well. However, this example applies the typical approach of FOL inference. The further relationships have then been modelled through a FOL rule. To prove the decisions for the proposed classifications, a small class hierarchy as prototype of the PPES is created as shown in Figure 7-2.

To ensure that no information is lost, the single concepts need to be associated using some additional object properties. The process only searches for concepts that have their root in the same original term. For each concept, a generic individual is assigned to differentiate whether the concepts refer to the same or to different individuals.

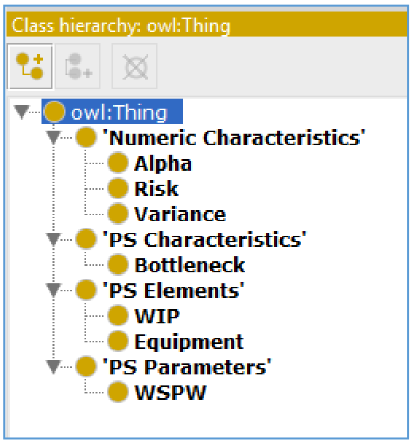


Figure 7-2: PPES Class Hierarchy Prototype

The following generic individuals can be assigned for the chosen example grouped by term:

1) Term 1:
    a. Individual of [Variance]: x
    b. Individual of [WSPW]: y
2) Term 2:
    a. Individual of [Risk]: x
    b. Individual of [Bottleneck]: y
    c. Individual of [Equipment]: y
3) Term 3:
    a. Individual of [Risk]: x
    b. Individual of [Bottleneck]: y
    c. Individual of [Equipment]: y
4) Term 4:
    a. Individual of [Alpha]: x
    b. Individual of [WIP]: y

Next, the grouped concepts are set into a logical order that follows the rule ‘concept B is existentially dependent on concept A’. This procedure follows the modelling guidelines of object-oriented software using the concept of compositions in UML. An existentially dependent object may only exist in reality if the master object exists as well (Balzert, 2011). For instance, a particular value for a stochastic variance can only exist if the according random variable exists. Thus, the concept that represents the random variable is the master object, whereas the variance is the existentially dependent object. The standard nomenclature to name object properties that link concepts which refer to different individuals is ‘has’ + ‘concept B’, where 'concept B' refers to the existentially dependent class. For some cases, it might be necessary to differ from this standard to ensure a clear meaning of the relationship that should be modelled. For cases where two concepts point to the same individual, no extra object property is required. When applying this procedure, the current example leads to the following derived object properties:

1) [hasVariance]: Object property that links [WSPW] to [Variance]
2) [hasRisk]: Object property that links [Bottleneck] to [Risk]
3) [hasAlpha]: Object property that links [WIP] to [Alpha]
4) [increase]: Object property that acts as generic relation between all kinds of classes

Figure 7-3 shows how the implementation of these associations works in Protégé.

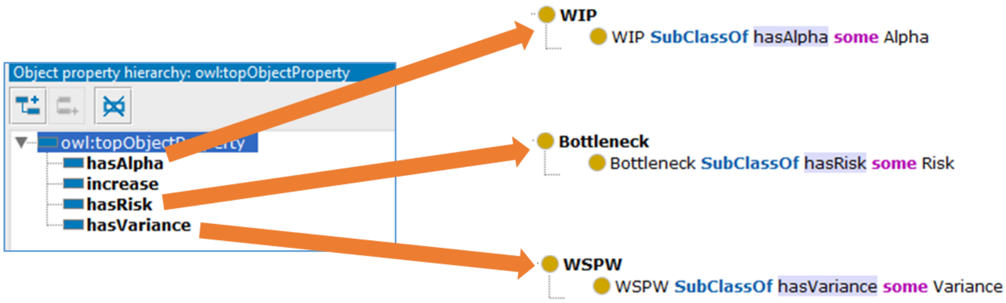


Figure 7-3: PPES Sample Relationships

Each class may consist of one instance to represent actual data, except the sub-classes of 'Logical Associations' which only act as controlling classes for the SWRL rules. Figure 7-4 shows the list of individuals for this test case.

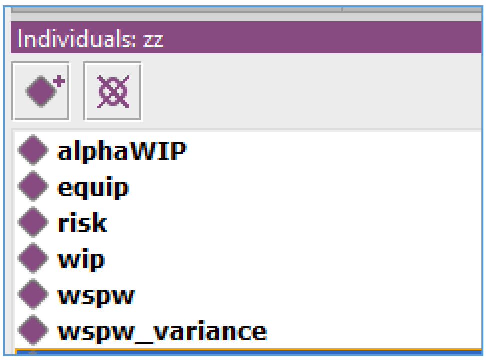


Figure 7-4: PPES Sample Individuals

The initial association gained by the case study data analysis had to be transformed into a SWRL rule. The detailed process of this transformation is discussed in 7.6. For demonstration purposes, the test case uses the following rules:

Rule 1:

$$WSPW(?x) \wedge Variance(?y) \wedge hasVariance(?x,?y) \wedge Equipment(?a) \wedge Bottleneck(?a) \wedge Risk(?b) \wedge hasRisk(?a,?b) \rightarrow increase(?y,?b)$$

Rule 2:

$$Alpha(?x) \wedge WIP(?y) \wedge hasAlpha(?y,?x) \wedge Bottleneck(?a) \wedge Equipment(?a) \wedge Risk(?b) \wedge hasRisk(?a,?b) \rightarrow increase(?b,?x)$$

The case study equipment master data indicates whether logistic procedures must treat a piece of equipment as a potential bottleneck or not. Thus, a risk for bottleneck shall only exist for individuals that are classified as ‘Equipment’ and additionally as ‘Bottleneck’. Since both ‘WSPW’ and its ‘Variance’ only consist of one instance, it would also be sufficient to directly call the individual instance ‘wspw_variance’ within the ‘increase’ predicate. However, looking at the later ontology usage, individuals may be changed, added or removed. To be resistant against a changing environment on an individual level, this generic style is the recommended way of modelling the SWRL rules. To prove the correct application of the ontology model and rules, the Protégé-internal reasoner has been executed. Figure 7-5 visualizes the currently defined associations between classes and individuals.

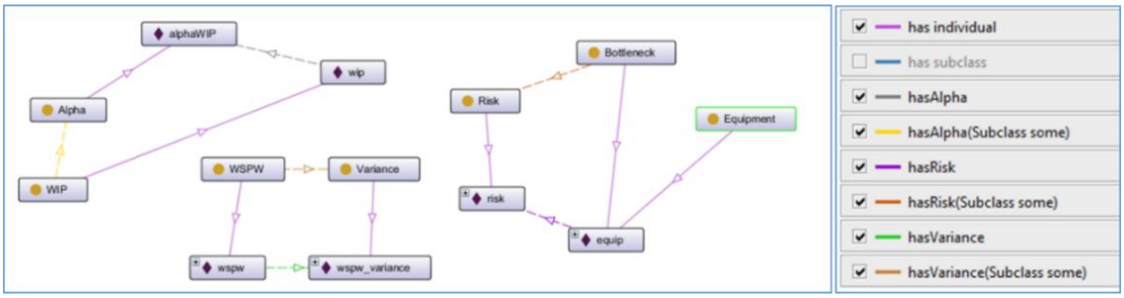


Figure 7-5: PPES Sample Associations between Classes and Individuals

The figure shows that no effective association via the object property ‘increase’ exists, at this time. By execution of the reasoner, Protégé computes these relations for the given individuals based on the specified rules. Figure 7-6 shows the results of this implication for the two individuals ‘wspw_variance’ and ‘risk’.

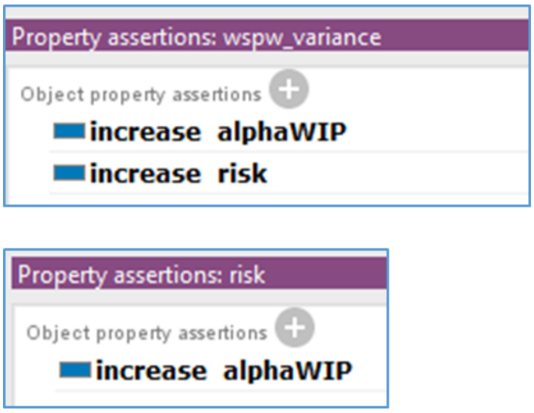


Figure 7-6: Inferred Object Property Relations for ‘increase’

In fact, the specified rules only cover the relations between ‘wspw_variance’ and ‘risk’ as well as between ‘risk’ and ‘alpha_wip’. Nevertheless, since the ‘increase’ property is marked as ‘transitive’, the inference engine automatically implies that ‘wspw_variance’ itself would increase ‘alpha_wip’.

The Protégé reasoner also provides explanations for these kinds of inferences. In this case, it even finds five ways to confirm this conclusion. Figure 7-7 shows one of them.

Figure 7-7: Explanation for inferred Relationships between Individuals

This example demonstrates that the intended procedure to create the classes as well as the rules works as expected. This way of modelling the ontology makes use of the strengths of both OWL and SWRL. After defining and implementing the entire PPES in Protégé, it is possible to perform such direct and transitive effect analyses based on the manifold SWRL rules.

The above transformation procedure is applied on all records of the data matrix and generates 178 unique concepts. However, after manual verification, not all of the proposed concepts can be used in a meaningful way. The following conditions have been applied to skip proposed concepts and consolidated them into a phrase that consists of multiple words:

1) Concepts are meaningless without further context.
   AND Concepts are not used in any further term.
2) OR two or more concepts belong together to maintain the meaning.

After applying these conditions, 56 concepts must be transformed into an expression that supports the standards of explicitness and importance to the study. All other generated concepts will be associated through object properties. The final list of concepts consists of 150 records. To achieve a standard speech within the ontology, each concept needs to be standardized into either plural or singular. A study on entity naming conventions for ontology leads to the recommendation to use singular. Reasons for this recommendation are the dominance of singular in existing ontologies and syntax restrictions in linear RDF notations such as N3[3]. However, the study also mentions that there might be cases where the plural is the more correct representation of a concept, for instance, if it indicates the proper noun or brand name of an object (Svátek and Sváb-Zamazal, 2010). Considering the naming and desired flexibility of object properties, it could potentially lead to grammatical or even logical confusion if the inference engine implies relations between individuals of different granularity. The transformation of concepts into singular applies the following rules:

1) If the plural is the more proper specification of the concept, keep the plural. The only valid conditions are an established proper noun, since the case study was not undertaken with brand names, and grammatical reasons, for instance, if a singular does not exist.
2) If a pure transformation into singular is possible without losing or distorting information, then use the simple kind of transformation based on the dictionary entry.
3) If a pure singular of a concept does not meet the criteria of rule #2, the concept is substituted by a singular synonym. If possible, an existing singular concept from the concepts table is used.

4) If a concept specification consists of a phrase whose head noun refers to a plural of something, the phrase is rearranged to refer to a singular of something

The analysis of the unique concepts leads to 118 singular records. According to the rules above, 27 concepts need to be modified. Figure 7-8 shows the distribution of the applied rules.

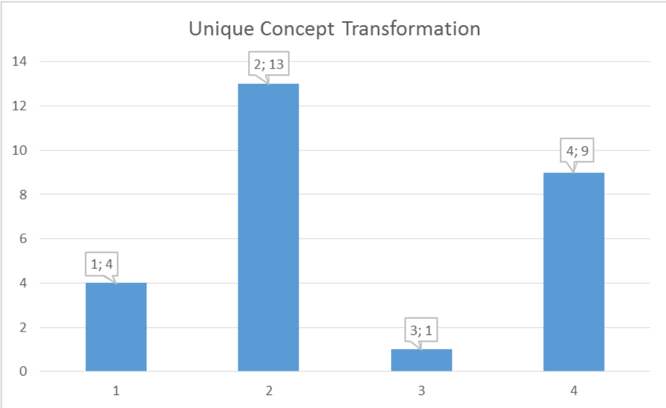


Figure 7-8: Unique plural Concept Transformation by Rule

As an additional result, the number of unique concepts could be reduced by four concepts due to substitution (rule #3), or since singular versions of the transformed concepts already exist (rule #2). As the next step, a newly created table associates the single concepts to their original terms using foreign keys on the term ID. The initial 134 terms are expressed through 281 partially combined concepts. A transposed table groups the data by source term to count the number of concepts that are required to express a term. Figure 7-9 shows the distribution of this query.

The figure visualizes that most of the terms can be verbalized either via one or two concepts. Only a minority of 25% requires three, four or even five concepts to cover the entire meaning of the term. For terms that require only one concept to cover their meaning, it is not necessary to create any linking object property. All other concepts will use object properties to refer to a parent term.

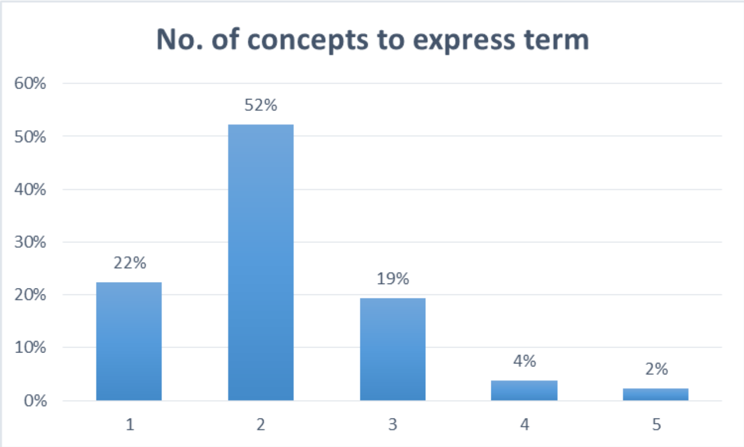


Figure 7-9: Number of Concepts to express Terms

As prerequisite to generate the entity tree as the primary hierarchy within the PPES, the identified concepts need to be classified by uniting classes. The project applies a hybrid approach to build the ontology hierarchy by applying bottom-up as well as top-down techniques. First, the bottom-up technique classifies the concepts at the lowest level. These classes later act as hierarchical groups within the tree. The process of classification is similar to the coding procedure and runs iteratively. Per procedure run, each concept is marked with a class that potentially unites multiple concepts into a common logical group. With this information in the ontology, the rules engine is able to consider individuals as similarly based on their common upper class, though the concept itself is different. Technically, a grouping class is also a concept. Such classifying concepts are not located at the deepest level of the ontology tree and have only a grouping function. By performing iterative runs, the procedure identifies relationships between classes. Each step in the procedure generates a more appropriate classification for the concepts because it introduces, modifies or rejects classifications. The procedure also reveals if some of the concepts are hierarchically related. After final evaluation of the classifications, the hierarchy tree can be developed in Protégé. This procedure is described in the next subsection when discussing the class hierarchy in particular.

Table 7-3 shows the first-level classifiers that are directly applied to the single concepts along with the number of associated concepts.

Table 7-3: First-level Classifiers on single Concepts

#	Classifier	Number of Concepts associated to Classifier
1	Machine-oriented Performance Indicator	20
2	PS Participant	18
3	Generic Characteristic	12
4	PS-oriented Performance Indicator	7
5	Calculation Result	7
6	Unit of Measurement	7
7	Employee-oriented Characteristic	7
8	Machine-oriented Characteristic	6
9	Manufacturing Incident	5
10	PdM Goal	4
11	EM	4
12	Manufacturing Method	4
13	Manufacturing Activity	4
14	Process-oriented Performance Indicator	4
15	PdM Element	4
16	Process-oriented Characteristic	3
17	Generic Performance Indicator	3
18	Success Factor	3
19	Downtime	3
20	WIP-oriented Characteristic	3
21	Logistics Method	3
22	Logistics Activity	3
23	PA	2
24	EM Strategy	2
25	PdM Characteristic	2
26	Research Method	2
27	PS Parameter	2
28	PdM Activity	2
29	PA Application	1
30	Thing	1
31	Business Performance Indicator	1
32	EM Process	1

These classifiers act as the major inputs to build the class hierarchy. The final step of the term transformation procedure is to mark single concepts as far as they are either equivalent or opposite to each other. Though the original terms have already been harmonized during the data analysis, the segmentation into concepts generates sub-terms, which can be logically related to other sub-terms. These associations support the ontology rules engine and increase the inference quality. For instance, the terms ‘Alpha Tool’ and ‘Equipment Reservations’ are not related up to now since no association has been stated by the experts. However, the word segmentation leads to following concepts:

1) [Alpha] + [Tool]
2) [Equipment] +[Reservations]

The case study results pointed out that the words ‘Tool’ and ‘Equipment’ are equivalent. Both concepts are classified as ‘Participant’ of the SI PS based on the 4M definition of Ishikawa. By storing this information in the ontology, the rules engine makes use of it to derive further axioms that experts have not yet identified. The previously assigned classes act as entry point for the algorithm that compares only concepts within the same class against each other. Based on the classification procedure, there is a high probability of finding logical relationships between single concepts from the same class. Moreover, it is expected that concepts from different classes are principally not related in terms of equivalence or opposition. Table 7-4 shows the concepts that have been marked as equivalent based on the case study information and context:

Table 7-4: Equivalent Concepts for PPES

Concept	Equivalent Concept	Reason
Alpha	Variability	From the Operating Curve formulas, ‘alpha’ is synonym to the variability of the 4M
Degree	Level	Both concepts express the maturity of something.
Equipment	Machine; Tool	All three concepts refer to the machine as participant of the 4M.
Failure	(Machine-Related) Process Failure	A ‘Machine-Related Process Failure’ is only some kind of failure of within a PS.
Inventory	WIP	‘WIP’ quantifies the shop floor inventory of wafers during the production process.
Process	Single Process	From the given term associations, ‘process’ always means ‘single process’.

The equivalence between concepts needs to be configured only in one direction. Protégé automatically derives the vice versa configuration for the second concept. Table 7-5 shows the concepts that have been marked as equivalent based on the case study information and context.

Like the equivalence, the contrariness between concepts needs only to be configured in one direction and Protégé adds the vice versa configuration to the second concept. At this stage, the term transformation into concepts is finished based on the proposed procedure. The generated data is then applied to build the class hierarchy for the ontology as discussed in 7.2.3.

Table 7-5: Opposite Concepts for PPES

Concept	Opposite Concept	Reason
Offline	Online	Both concepts are linguistic antonyms.
Dependency	Independency	Both concepts are linguistic antonyms.
Downtime	Uptime	Both concepts are linguistic antonyms.
Evenness	Unevenness	Both concepts are linguistic antonyms.
Preventive Maintenance	Reactive Maintenance	In EM, preventive means a strategy where maintenance actions are performed prior to the failure, whereas reactive means that maintenance actions get performed once a failure has happened. In this context, both concepts are opposite.
Scheduled Down	Unscheduled Down	If machine downtimes are consciously planned by responsible persons, they are called 'scheduled'. Otherwise, an unplanned downtime is called 'unscheduled'.
Scrap	Yield	Yield quantifies the good parts of a wafer, whereas scrap quantifies the bad parts.
Stability	Variability; Alpha	From mathematical perspective, the variability is the extent to which a distribution is stretched or squeezed. 'More variable' means that data from a random variable is spread by a higher factor. In the context of operating curve, 'more stable' means that the data is less spread. Thus, stability is treated as antonym against variability and alpha.

7.4 Class Hierarchy and Specifications

The class hierarchy is an important aspect of the ontology since it owns the fundamental information about the similarity of concepts. Different approaches exist to build hierarchies for an ontology. Depending on the number of unique concepts, a hierarchy can be generated manually by defining generalizing classes or connecting concepts in terms of hierarchical dependency. Automatic approaches are the flat clustering and the hierarchical clustering as methods from DM and machine learning. This section discusses the different ways of generating ontology hierarchies to identify the method that best meets the requirements.

An established method for flat clustering is the k-means algorithm. A given training set $x^{(1)}, \ldots, x^{(m)}$ needs to be grouped into a few cohesive clusters. Each data point $x^{(i)} \in \mathbb{R}^n$ consists of a feature vector but no label. Thus, this kind of procedure is called unsupervised learning. The goal of the algorithm is to predict *k* centroids and a label $c^{(i)}$ for each data point. Thus, concepts with less distance in between are candidates for the same cluster. A distance can be expressed through the feature vector that is part of an n-dimensional data matrix. The algorithm works as follows (Ng and Piech, 2013):

1) Initialize cluster centroids $\mu_1, \mu_2, \dots \mu_k \in \mathbb{R}^k$ randomly
2) Repeat until convergence:

{

For every *i*, set

$$c^{(i)} := \arg min \left|\left|x^{(i)} - \mu_j\right|\right|^2$$

j

For each *j*, set

$$\mu_j = \frac{\sum_{i=1}^{m} 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^{m} 1\{c^{(i)} = j\}}$$

}

First, the data must be prepared to apply the algorithm. K-means algorithm requires feature vectors to measure the distances. A data matrix needs to provide vectors that describe the relationships between concepts and term associations as visualized in Table 7-6:

Table 7-6: Schematic on Clustering Data Matrix

	Assoc X	**Assoc Y**	**Assoc Z**
Concept A	0	0	1
Concept B	1	0	0
Concept C	1	0	1

If a concept is part of an association, the cell value equals 1, otherwise it equals 0. The procedure generates the following vectors for this example:

$$A = (0 \quad 0 \quad 1)$$

$$B = (1 \quad 0 \quad 0)$$

$$C = (1 \quad 0 \quad 1)$$

When applying this procedure to the real concepts and terms, it creates a 150x272 data matrix. A particular k-means algorithm has been developed in Python. As the first step, the most accurate value for *k* needs to be identified as the number of target clusters for the bottom level. To evaluate the best value for *k*, the Python program runs several iterations on the matrix. Figure 7-10 shows how the cluster score improves by increasing *k* from 1 to 150.

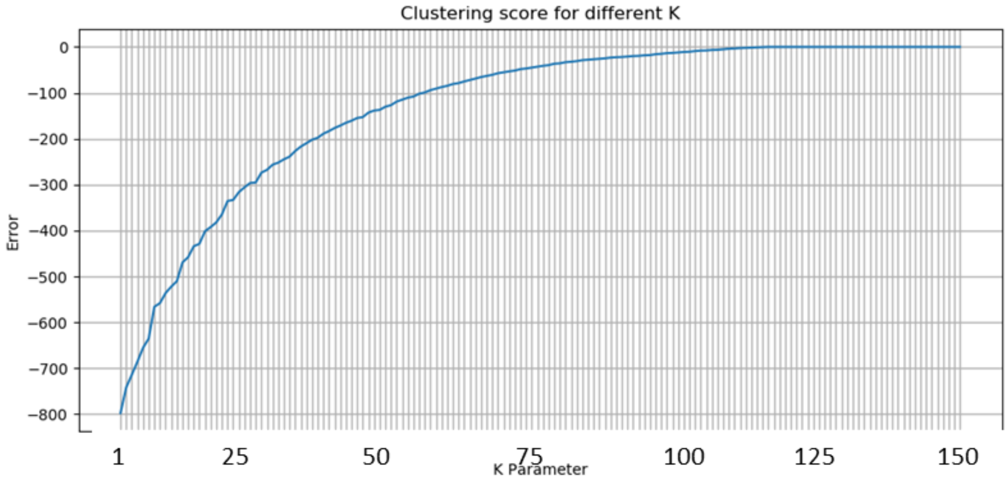


Figure 7-10: Clustering Score for different *k*

The error distance to zero is an indicator for the matching accuracy of the calculated clusters. A small distance means little deviation, and the clustering score tends to zero by increasing k. The mathematical reason for this is that k=150 means that 150 concepts are grouped into 150 clusters. Thus, no error occurs since each concept is associated with itself. However, such detailed clusters would not produce any benefit to the ontology. Assuming that the k-means algorithm groups the concepts only by one hierarchy level, a smaller value for k needs to be identified to generate useful and disjoint clusters. Python allows for running further iterations on the data matrix that have the same value for k. This is important to find the best fitting positions for the centroids and to analyse whether the error distance is stable or spread. A sufficient value for k means that the error distances are near to zero among the iterations. With this iterative procedure, the k-means algorithm is continuously refining the clusters and altering the centroids. Figure 7-11 shows the results of 15 iterations for *k*=20 on the data matrix.

The maximum error distance between all iterations is approximately 20 and, compared to the overall trend from Figure 7-10, relatively stable. Figure 7-12 shows the results from a further scenario with *k*=50. This scenario could reduce the error distance to approximately 3 over all iterations, which is a significant improvement compared to *k*=20. When the number of target clusters were increased by a factor of 2.5 the error distance was reduced by the factor of 0.85.

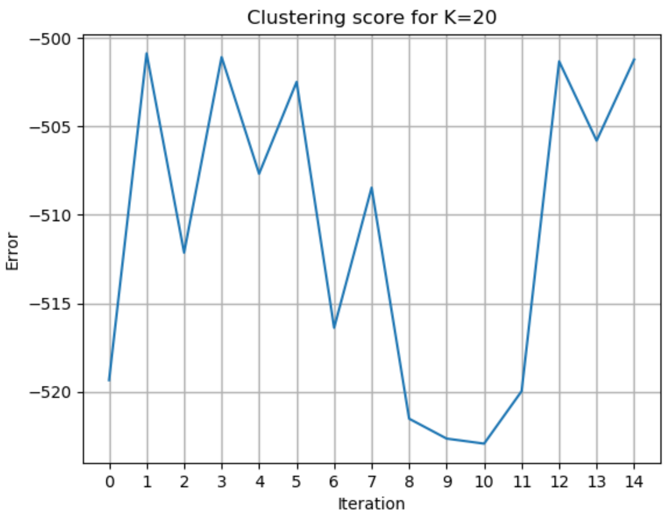


Figure 7-11: Clustering Score for *k*=20

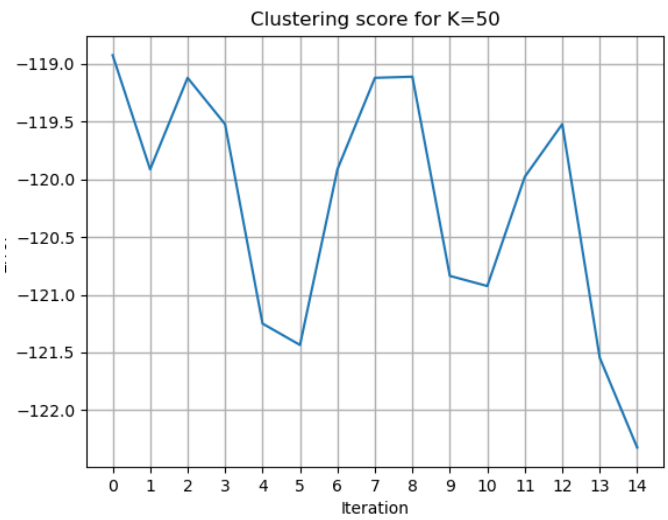


Figure 7-12: Clustering Score for *k*=50

Another scenario with *k*=100 demonstrates what happens to the error distance with an increasing number of target clusters. Figure 7-13 shows the results from the calculation. The scenario shows that the error distance is only approximately 1, which again shows a significant reduction compared to *k*=50.

Next, an evaluation of how useful the generated clusters are for this particular ontology was carried out. Since the algorithm input comes from linguistic data, different criteria are required to measure the cluster quality than that for numerical data.

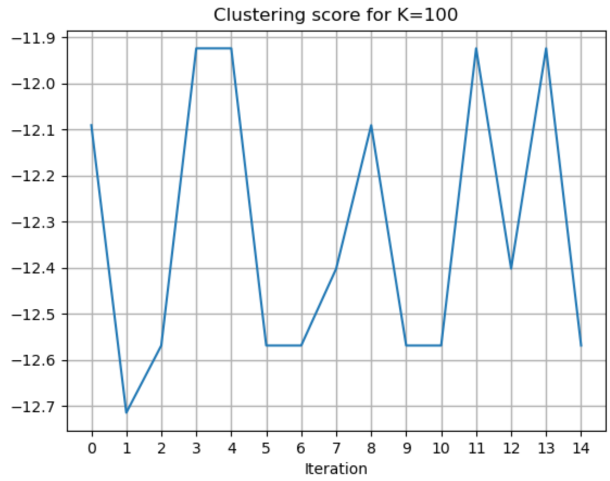


Figure 7-13: Clustering Score for *k*=100

Schulte im Walde (2003) pointed out that the size of a cluster is an important criterion. The entire data set should not be associated to only one single cluster. Further, the algorithm should not only generate clusters that consist of only one concept. It is rather intended to find a result that provides a well-balanced clustering in combination with a minimum of prediction errors. When $|C_x|$ is the number of concepts per cluster C_x, n is the number of clusters generated from the algorithm, and m is the number of all existing concepts, then, following cumulative functions q_{cl} and q_{co} can be defined:

Accumulation of the single cluster percentages as defined in Equation (7.1).

$$q_{cl} = \sum_{x=1}^{n} \frac{1}{n} \tag{7.1}$$

Accumulation of the concept per cluster percentages as defined in Equation (7.2).

$$q_{co} = \sum_{x=1}^{n} \frac{|C_x|}{m} \tag{7.2}$$

In a theoretical scenario where the degree of balance is at its maximum, the course of both functions is identically linear and they are fully overlapping in the case that $n < m$. However, having linguistic data, there can be concepts that the algorithm cannot group together with others. Thus, the theoretical optimum for clustering is not realistic for this type of data. The algorithm results are analysed according to their quality to find the best fitting one for this project. To make the results comparable despite the different number of clusters, the absolute results are transformed into percentages. Figure 7-14 shows the courses of q_{cl} and q_{co} for different values of k as pareto chart to compare the results.

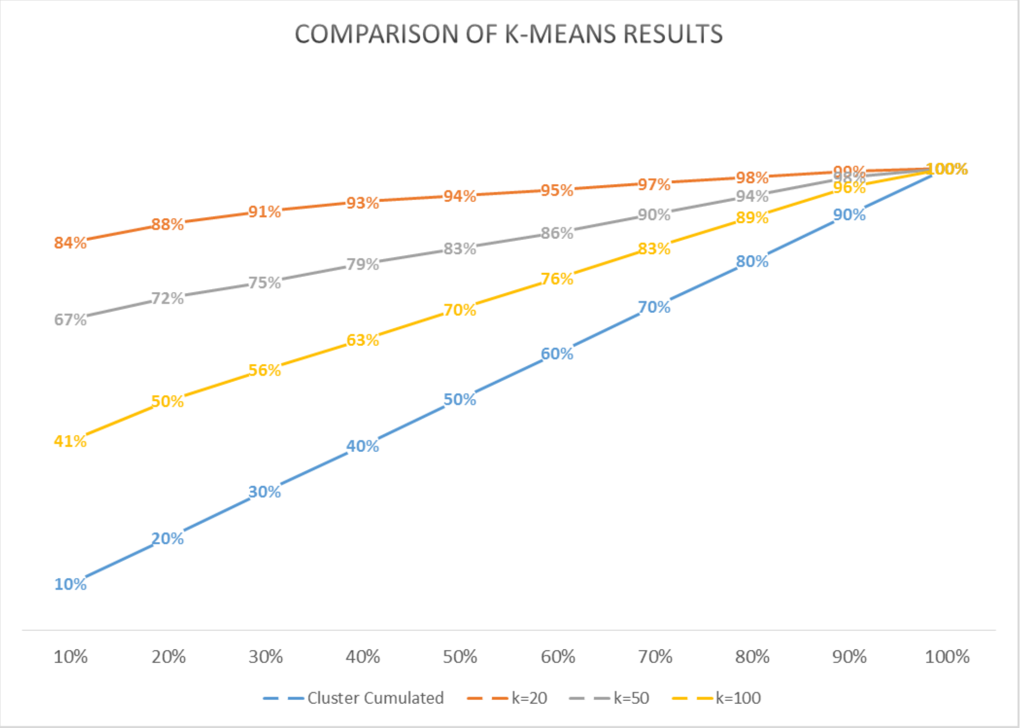


Figure 7-14: Pareto Comparison of k-means Results

For each scenario, the generated clusters are ordered by | C_i | descending. Thus, the largest clusters are listed first. The courses of the different curves for q_{cl} show that the algorithm results in an unbalanced clustering for the given data matrix. The biggest 10% of all clusters already consist of 41%, 67% and 84% of all concepts. To measure the quality, the average distance of each curve to the optimum curve is calculated.

An additional criterion for the quality is the percentage of clusters that only consist of one concept. Figure 7-15 shows the results from this evaluation. The lowest average error can be found for k=100. Admittedly, the reason for this is the relatively high number of generated clusters. This leads to 83% of all clusters that consist of only one concept and the accumulation is increased quite linearly for them. Though the error is even higher for k=50, the percentage of single clusters is almost the same. The significant disadvantage of k=20 is the generation of fewer but very large clusters. Thus, a majority of all concepts is clustered together and the rest is grouped into clusters that consist of only one concept. The comparison demonstrates that an increasing value of *k* tends to result in a high percentage of clusters that consist only of one concept, whereas a decreasing value of *k* tends to show a high percentage of concepts which are part of one single cluster. From the given results, the candidate for the most appropriate ontology classification is *k*=20.

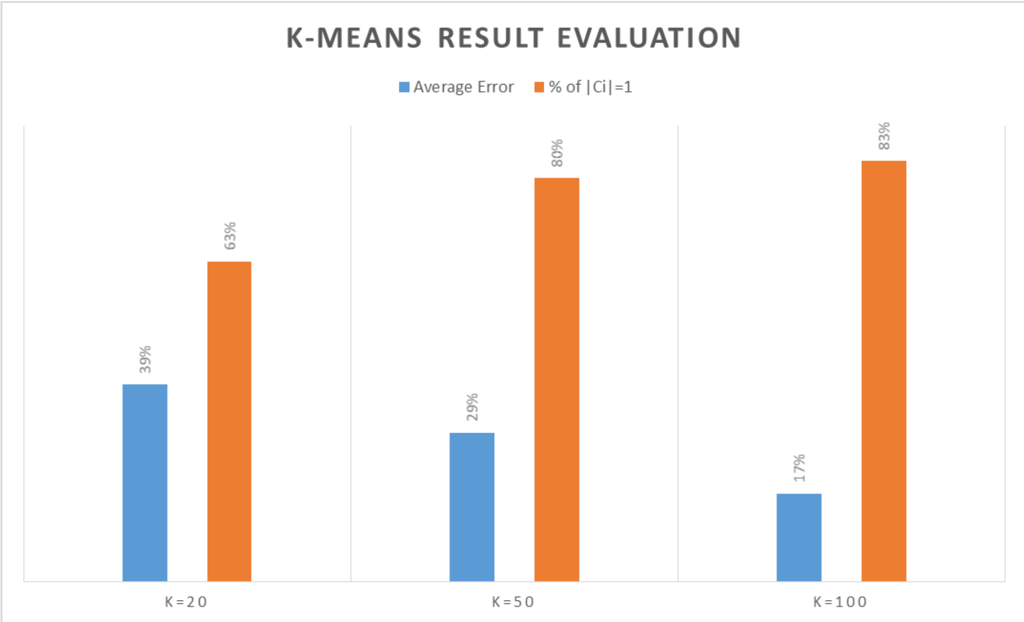


Figure 7-15: K-means Result Evaluation

In the next step, one can test if the hierarchical clustering generates better results. The idea of this approach is to build a multi-level binary tree of the data that successively merges similar groups of points. The so-called agglomerative clustering (AC), firstly, places each data point into its own singleton group and, then, merges iteratively the two closest groups until all the data are merged into a single cluster. This kind of approach is bottom-up since it starts at the single concept (Blei, 2008). It is also possible to start this kind of automatic clustering top-down with a technique called divisive clustering. Here, all concepts are firstly put together into one cluster. Then, the cluster is split using a flat clustering algorithm. The algorithm repeats this procedure recursively until each concept is in its own singleton cluster. Due to the need for a flat clustering algorithm as subroutine, the top-down approach is conceptually more complex than bottom-up. In fact, both approaches are useful for mass data and text mining challenges and require knowledge of distances between data points. The less expensive bottom-up approach was selected for this study since the literature does not provide significant advantages for the top-down approach with regards to this project. AC does not necessarily require a target value for *k*. However, depending on the particular use case, it can make sense to define a meaningful number of partitions to cut the data. Based on the literature, the following criteria can be considered when choosing a value for *k* (Manning et al., 2018):

1. Data may be cut at a pre-specified level of similarity that can be high or low.
2. Data may be cut where the gap between two successive combination similarities is largest. Such large gaps are typical indicators for natural clusters and the addition of one more cluster would decrease the algorithm quality significantly.
3. Identify *k* via a specific equation that is published in literature.

As in flat clustering, *k* can also be pre-specified manually to generate the cutting points.

Through software tools such as Python and its scientific libraries, it is possible to perform several runs on the data with varying values for *k* to identify the best result quality. Particularly with a small amount of data, it does not require many computing resources. Thus, the approach mentioned in point 3 can be easily applied to this study if a target value for *k* is seen as required. The most relevant aspects of the AC are the selection of metric and linkage criteria. Linkage is a required parameter for the AC algorithm to determine which distance should be used preferably between two sets of observations. The scikit-learn library provides following criteria (Pedregosa et al., 2011):

- Ward (only applicable for Euclidean distance as metric): minimizes the variance of the clusters being merged.
- Average: uses the average of the distances of each observation of the two sets.
- Maximum (or complete): uses the maximum distances between all observations of the two sets.

- Single: uses the minimum of the distances between all observations of the two sets.

Metrics are important to select the mathematical method of distance calculation and to compute the linkage. While some more equations are mentioned in literature, the scikit-learn library for Python has the following metrics for AC distances:

- Euclidean
- Manhattan
- l1
- l2
- Cosine
- Precomputed

Testing was carried out on which of the metrics, linkages and different combinations of both generates the best results for the given data matrix. A simple AC algorithm requires following variables and parameters:

- A *N* x *N* similarity matrix *C*
- A list of merges from the clustering *A*
- An identifier *I* to recognize clusters that are still available
- A function *SIM(I, m, j)* that computes the similarity of cluster *j* with the merge of clusters *i* and *m*

Figure 7-16 (Manning et al., 2018, p. 381) shows an AC algorithm using this information:

```
SimpleHAC(d_1, ..., d_N)
for n ← 1 to N
do for i ← 1 to N
    do C[n][i] ← Sim(d_n, d_i)
    I[n] ← 1  (keeps track of active clusters)
A ← []  (assembles clustering as a sequence of merges)
for k ← 1 to N − 1
do ⟨i, m⟩ ← arg max_{⟨i,m⟩: i≠m ∧ I[i]=1 ∧ I[m]=1} C[i][m]
    A.Append(⟨i, m⟩)  (store merge)
    for j ← 1 to N
    do C[i][j] ← Sim(i, m, j)
        C[j][i] ← Sim(i, m, j)
    I[m] ← 0  (deactivate cluster)
return A
```

Figure 7-16: AC Algorithm (Manning et al., 2018, p. 381)

Next, the AC algorithm from the scikit-learn library for Python is applied to the to the data matrix using different configuration scenarios. Beyond the particular clusters and associations with the concepts, an AC result can also be visualized in much more detail as a hierarchical dendrogram. Figure 7-17 shows a dendogram that Python generated based on the data matrix using the metric ‘precomputed‘ and the linkage ‘average‘.

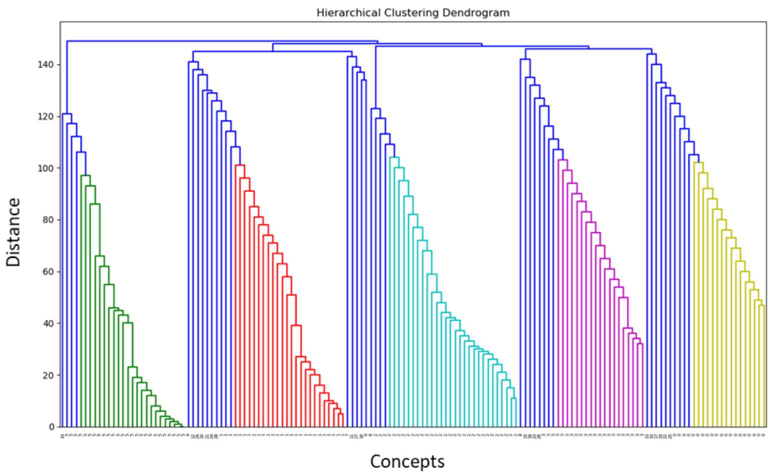


Figure 7-17: Specific Dendrogram for the AC on the Data Matrix using Pre-computed and Average

In a dendrogram, each horizontal line refers to one merge. The value of the horizontal line on the y-axis represents the similarity between the two clusters. The higher the value, the less similar are the two clusters. With these results, AC does not only provide knowledge about the similarity between single concepts, but furthermore between clusters. A dendrogram also reveals the significant differences between the single configurations.

When applying an AC using the metric “Manhattan” and the linkage “complete”, the cluster hierarchy looks very different. Figure 7-18 shows the dendrogram that was created from this configuration. Obviously, the distribution of the clusters and merges appear different to the previous configuration. A comparison of the results of AC in a quantitative way requires analysing the quality of the clustering result using the same procedure as for k-means. Furthermore, this standardized procedure allows a direct comparison of AC to k-means. The comparison is limited to only a few ways of configuration to demonstrate the different results. In the case of a well-fitting result, the particular configuration could be refined to improve the clustering.

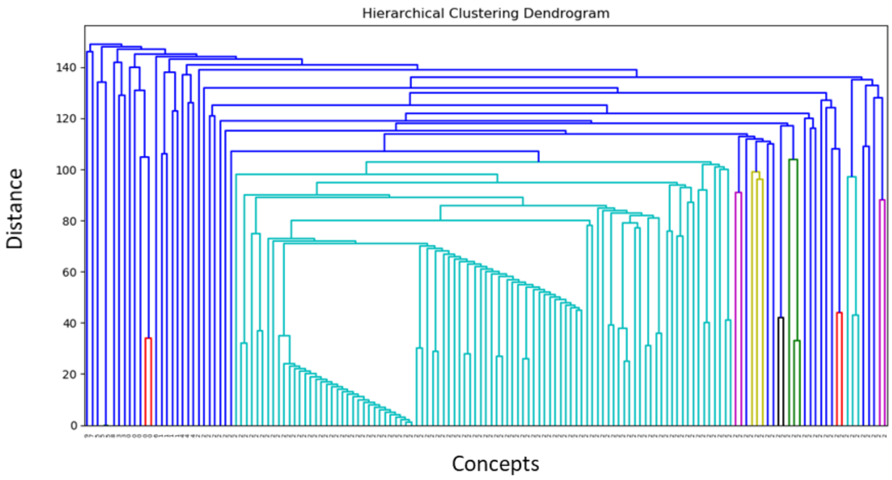


Figure 7-18: Specific Dendrogram for the AC on the Data Matrix using Manhattan and Complete

Figure 7-19 shows the courses of q_{cl} and q_{co} for different AC configurations as a Pareto chart to compare the results.

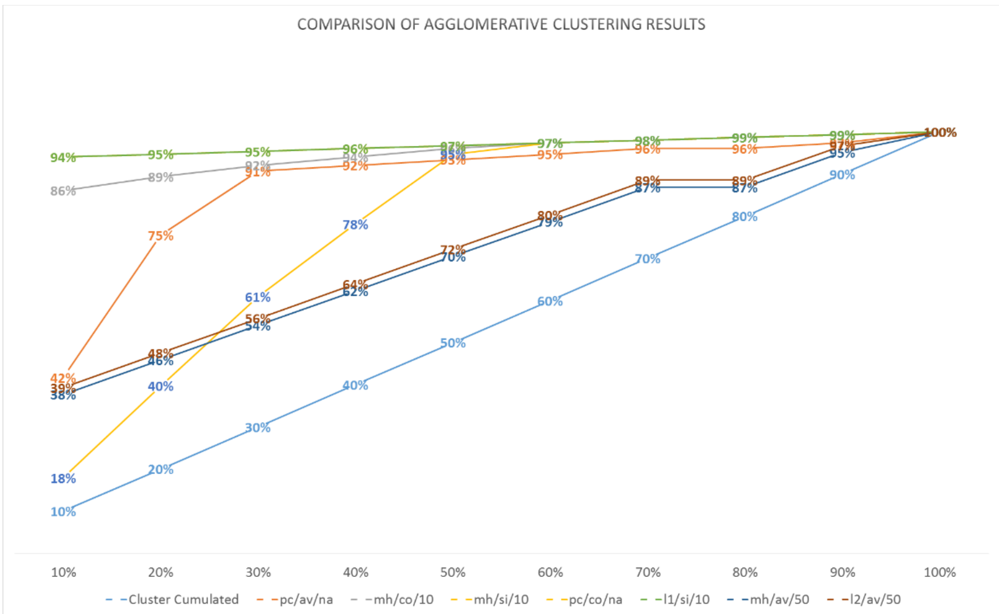


Figure 7-19: Pareto Comparison of AC Results

The configurations differ in metric, linkage as well as target number of clusters. In particular, for AC with only 10 target clusters, a similar course for

q_{co} can be identified: A very small number of clusters already contains the most concepts. For the metric “precomputed”, it is not necessary to specify target clusters since it generates an optimum number of clusters by itself. AC configurations with *k*=50 tend to give a rather linear course for 70% of the largest clusters. Next, the mean errors of each configuration are calculated and combined with the percentage of clusters that consist of only one concept. Figure 7-20 presents the AC result evaluation.

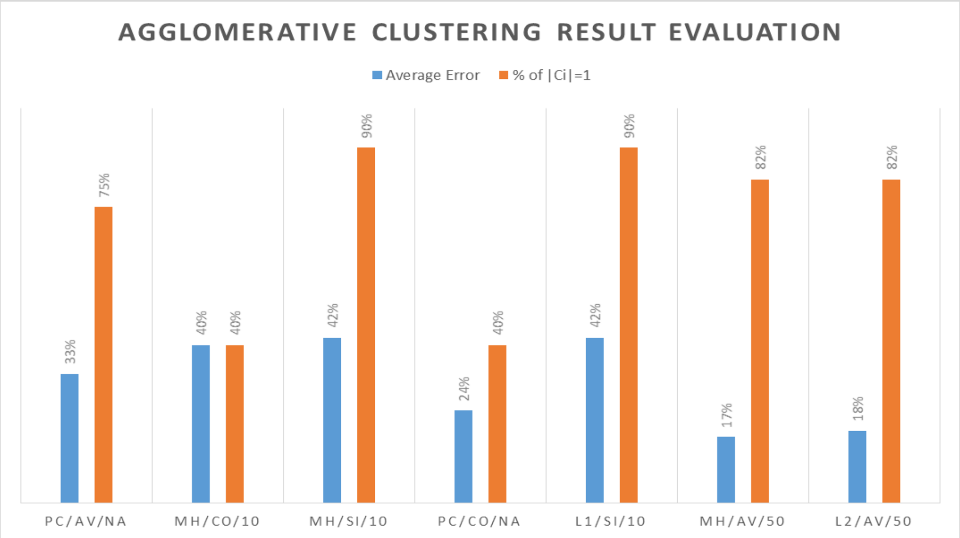


Figure 7-20: AC Result Evaluation

The evaluation shows that configurations with *k*=50 tend to give a more balanced clustering. However, the percentage of clusters with only one concept is perceptibly high. Compared to k-means, this effect cannot be reduced by decreasing the value of target clusters – the percentage grows even more. The most effective results can be achieved with the metric “pre-computed” and the linkage “complete” as this configuration leads to the lowest average error and lowest percentage of single clusters. Thus, it is a candidate for the final classification structure of the ontology.

As discussed in 7.3, another method to create clusters is the manual creation by applying coding techniques. Table 7-3 lists the manually generated clusters at the lowest level and the number of concepts per cluster. This result can be compared with the candidates from k-means and AC to find the most effective clustering approach for this ontology. Figure 7-21 depicts this result comparison.

The figure clearly illustrates that the manually generated clusters provide the best results in terms of balancing and percentage of single clusters. Thus, the project will apply the classifiers from Table 7-3 to build a bottom-up hierarchy. This process will apply the coding technique iteratively on the classifiers until no further grouping is logically possible or useful.

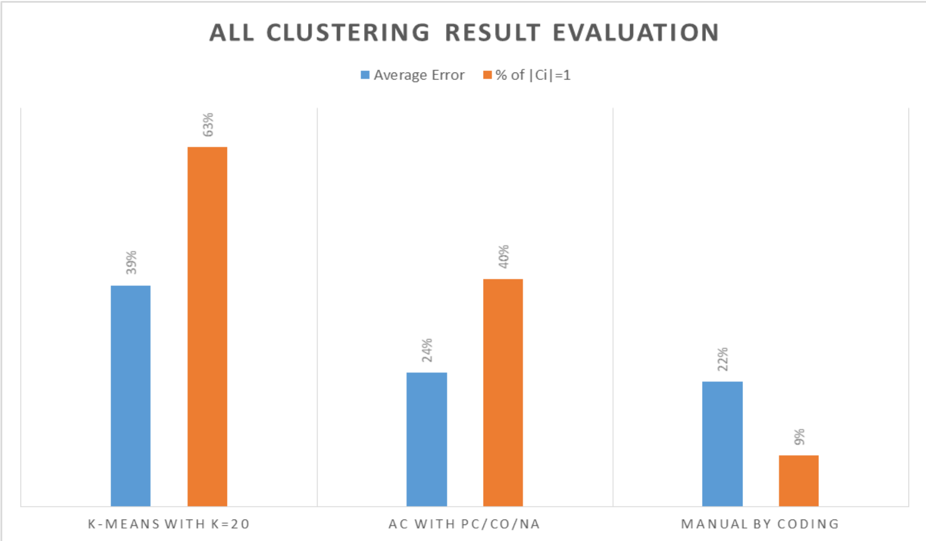


Figure 7-21: Final Comparison of all Clustering Approaches

Table 7-7 shows the results from this iterative coding process from the lowest class level 1 until the root class level 6.

Since the creation strategy is bottom-up, each class level represents the level of the hierarchy from a single concept perspective. An ‘x’ is used to specify that the classifier to the left is already at the highest level of the ontology hierarchy, and it will not be clustered anymore. The final PPES hierarchy consists of 182 entities, which are consistently connected through six levels. The definition of the PPES hierarchy is imported to Protégé to technically generate the PPES entities and hierarchical relationships. Next, the definitions of synonyms and antonyms from the previous chapter need to be configured. For synonyms, Protégé provides the default setting ‘Equivalent To’ per concept. For antonyms, there exists no direct setting in the software, however, ‘Disjoint With’ can be used instead. It does not particularly state that two concepts are opposite; nevertheless, an instance of one concept is not allowed to be an instance of the other concept at the same time. After this configuration, the class hierarchy and entity specification is finished. The next subsection discusses the creation of object properties and their technical integration to the PPES.

Table 7-7: Manually created Class Hierarchy

#	Class Level1	Class Level2	Class Level3	Class Level4	Class Level5	Class Level6
1	Machine-oriented Performance Indicator	Performance Indicator	PS	x	x	x
2	PS Participant	PS	x	x	x	x
3	Generic Characteristic	Characteristic	PS	x	x	x
4	Unit of Measurement	X	x	x	x	x
5	PS-oriented Performance Indicator	Performance Indicator	PS	x	x	x
6	Calculation Result	X	x	x	x	x
7	Employee-oriented Characteristic	Characteristic	PS	x	x	x
8	Machine-oriented Characteristic	Characteristic	PS	x	x	x
9	Manufacturing Incident	X	x	x	x	x
10	PdM Goal	PA Application	PA	x		x
11	Manufacturing Method	Method	PS	x	x	x
12	Process-oriented Performance Indicator	Performance Indicator	PS	x	x	x
13	PdM Element	PA Application	PA	x	x	x
14	Manufacturing Activity	Activity	PS	x	x	x
15	EM	Method	PS	x	x	x
16	Generic Performance Indicator	Performance Indicator	PS	x	x	x
17	Logistics Activity	Activity	PS	x	x	x
18	Process-oriented Characteristic	Characteristic	PS	x	x	x
19	WIP-oriented Characteristic	Characteristic	PS	x	x	x
20	Success Factor	Manufacturing Method	Method	PS	x	x
21	Logistics Method	Method	PS	x	x	x
22	Downtime	Machine-oriented Performance Indicator	Performance Indicator	PS	x	x
23	PdM Activity	PA Application	PA	x	x	x
24	PA	x	x	x	x	x
25	PS Parameter	PS	x	x	x	x
26	PdM Characteristic	PA Application	PA	x	x	x
27	EM Strategy	EM	Manufacturing Method	Method	PS	x
28	Research Method	Method	PS	x	x	x
29	PA Application	PA	x	x	x	x
30	EM Process	EM	Manufacturing Method	Method	PS	x
31	Business Performance Indicator	Performance Indicator	PS	x	x	x

7.5 Object Properties

Concepts may have different purposes within an ontology depending on the overall use case. When associating concepts through object properties, it is important to think of a specific individual that is assigned to these concepts. The PPES ontology needs to distinguish between two cases:

1) An individual can be classified as concept A and, in parallel, as concept B.
    a. Example: An individual can be an employee and can also have the job role of engineer. Thus, one individual is classified as concept ‘Employee’ plus as concept ‘Engineer’.
    b. In such cases, no object property is required to associate both concepts. The association in SWRL is realized via logical conjunction. In OWL such concepts are mostly part of the same hierarchy branch.
2) An individual can be classified as concept A and is additionally described via an individual that is classified as concept B.
    a. Example: An individual can be an operator and can have a certain qualification level. An individual from a concept ‘Qualification Level’ refers to a set of professional skills or certificates that can be assigned to many individuals who are classified as concept ‘Operator’. Thus, the sets of individuals of both concepts are disjoint.
    b. In such cases, an object property is required to assign the major concept ‘Operator’ to the existentially dependent concept ‘Qualification Level’. This concrete object property is named ‘hasQualificationLevel’.

The analysis leads to 19 relationships between concepts from 16 terms that point to the same individual per term. These concepts do not require any object property. For the other groups of concepts that consist of more than one concept and different individuals, 55 unique object properties have to be generated. Some of the object properties are also shared between different concepts. Figure 7-22 shows the distribution of shared object property usage over all terms.

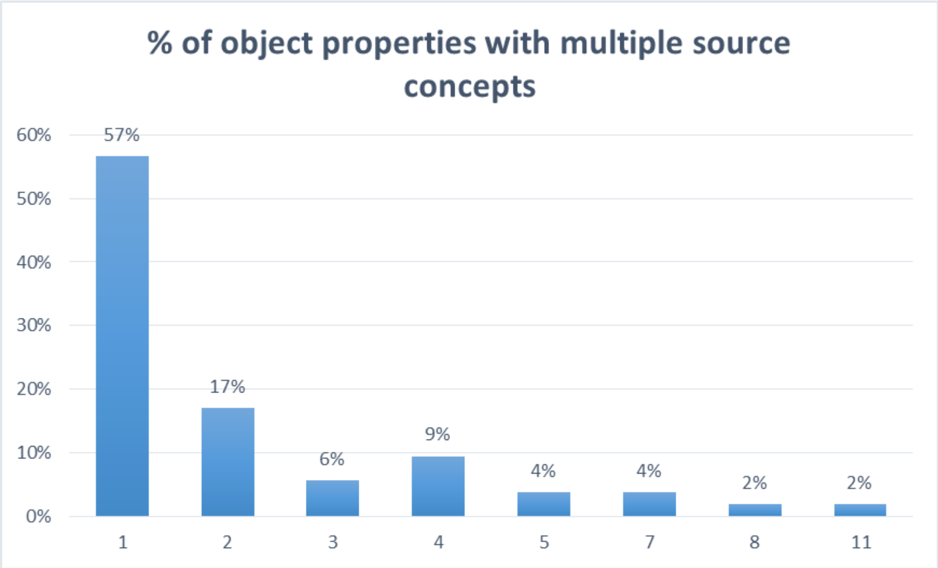


Figure 7-22: Distribution of shared Object Property usage over all Terms

The figure shows that a significant percentage of 43% of all object properties is shared between more than one pair of concepts. Thus, it is important to configure these relationships properly in order to gain high quality results from the inference engine. Protégé provides the following characteristics which need to be considered for each property (Musen, 2018):

1) **Functional**: The property is treated as a function that can only return one specific value for any given individual. If such a property points from a certain individual to more than one target individual, the inference engine implies that all target individuals denote the same object.
2) **Inverse Functional**: If the property has defined an inverse property, this inverse property is treated as functional, even though it would not be specified like that explicitly. Inverse functional properties are considered to have only one ingoing association, thus, a target individual may only be associated with one source individual. If more than one source individual points to the same target individual, the inference engine implies that those source individuals denote the same object.
3) **Transitive**: If an object property is marked as transitive and defines relations between three individuals x, y and z, where x is related to y and y is related to z, then the inference engine automatically creates a

relationship between x and z. This feature is useful for object properties with very generic purposes.

4) **Symmetric**: This characteristic specifies that if an individual x is related to an individual y, then y must also be related to x having the same property.
5) **Asymmetric**: This kind of setting is the opposite of symmetric and, consequently, means that two individuals can only be related to each other in one direction along the same property.
6) **Reflexive**: If an individual has a relation to itself, an object property needs to be set as reflexive. This means that this object property is not intended to point to any different target individual. Otherwise, the inference engine will assume that both individuals denote the same object.
7) **Irreflexive**: This characteristic specifies that an object cannot be related to itself via this particular object property.

Object properties can be further described by domain and range. This is important to support the inference engine. A domain is defined as one or many classes from the ontology hierarchy whose individuals are able to act as source within this particular relation. The range of a property is defined as one or many classes from the ontology hierarchy whose individuals are allowed to be related to an individual from the specified domain. However, domains and ranges are no restrictions. The inference engine uses this information to imply that different individuals from different classes are also part of the other class. Since the ontology makes use of disjoint classes, this might lead to inconsistencies (Horridge et al., 2007). Thus, this specification will not be applied. An accurate way to specify relations between concepts through object properties and to restrict inconsistent usage of individuals is the proper selection of cardinalities. OWL allows the description whether a class of individuals has at least, at most, or exactly a specified number of relationships with other individuals. The particular features in Protégé which support this kind of specification are called ‘Minimum Cardinality Restriction’ $(x \geq y)$, ‘Maximum Cardinality Restriction‘ $(x \leq y)$ and ‘Cardinality Restriction‘ $(x = y)$. This kind of setting, however, is only optional. It does not have to be configured if there is no realistic count of relationships that it should be checked against. Restrictions on object properties can also be generated through logical quantifiers. Similar to FOL, OWL provides an existential and universal quantifier restriction. Existential restrictions describe classes of individuals that participate in at least one relationship along a specified property to individuals that are members of a specified class. The keyword to denote this kind of restriction in Protégé is 'some'. Universal restrictions describe classes of individuals that for a given property only have relationships along this property to individuals that are members of a specified class. The keyword to denote this kind of restriction in Protégé is 'only' (Horridge et al., 2007).

All of these specifications need to be considered for the identified object properties. Nearly all of the properties share the same selection of characteristics, which is functional, asymmetric and irreflexive. The main reason for this is the word segmentation procedure and the narrow way of describing the relations. This leads to the following restrictions:

- Only one target individual is allowed for a certain source individual.
- Properties are not intended to express transitive relations.
- Properties define a certain direction, thus, only one direction is allowed for a relation between two individuals.
- Individuals are not allowed to become associated recursively.

Only for the object properties 'increase' and 'decrease' which are derived from the causal loop associations are the characteristics different, in order to support the generic usage within the PPES. They do not follow the previous restrictions to perform concatenated impact analyses. Although both properties could generate transitive information, the particular characteristic would not work correctly in this case. The reason for this is that OWL does not allow a proper definition of negations between object properties. Thus, the reasoner ignores the actual semantics of 'increase' and 'decrease' as well as their opposite character. However, Section 7.6 describes the modelling technique for this type of transitive concatenation with FOL.

The object properties use only existential quantifiers with a cardinality of x = 1 or x >=1 depending on the business requirement. For instance, a particular failure can have exactly one probability whereas it can have multiple risks.

Although each ontology class may consist of multiple individuals, a specific individual from a domain class is only allowed to be related to exactly one individual from the given range class using these object properties. For the object properties ‘increase’ and ‘decrease’, no further specification is required in terms of quantification and cardinality during the initial configuration. Since the concrete relationships between concepts are modelled with SWRL, this kind of specification is added to the rules.

After finalizing the object property specifications, the object properties can be created technically in Protégé.

7.6 First-Order Logical Model Propositions

This section describes the process to consolidate the previous results and explains how to develop a first-order logical PPES. Based on the steps that have been presented in the previous sections, it is possible to transform the initial terms into FOL language. These transformed terms can be set into relation using the identified associations from the case study. The terms are classified by PS, machine, process, EM, operator, costs and others. Table 7-8 shows the raw terms and their FOL transformations for general PS-oriented terms.

Table 7-8: PS-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
4M Synchronicity	4M(?a) ^ Synchronicity(?b) ^ hasSynchronicity(?a,?b)
Alpha PS	PS(?b) ^ Alpha(?a) ^ hasAlpha(?b,?a)
Alpha WIP	WIP(?b) ^ Alpha(?a) ^ hasAlpha(?b,?a)
CT	CT(?a)
CT Variance	CT(?a) ^ Variance(?b) ^ hasVariance(?a,?b)
Degree Of Dispatcher Compliance	DispatcherCompliance(?b) ^ Degree(?a) ^ hasDegree(?b,?a)
Degree Of Knowledge Of Engineers About Factory Physics	Engineer(?c) ^ Knowledge(?a) ^ hasKnowledge(?c,?a) ^ FactoryPhysics(?a) ^ Degree(?b) ^ hasDegree(?a,?b)
Degree Of Performance Synchronicity Between Similar Machines	MachineGroup(?b) ^ PerformanceSynchronicity(?a) ^ hasPerformanceSynchronicity(?b,?a) ^ Degree(?c) ^ hasDegree(?a,?c)
Degree Of Unevenness In WIP Distribution	WIPDistribution(?c) ^ Unevenness(?b) ^ hasUnevenness(?c,?b) ^ Degree(?a) ^ hasDegree(?b,?a)
Deliverability	Deliverability(?a)
DGR	DGR(?a)
Dispatcher Maturity	Dispatcher(?a) ^ Maturity(?b) ^ hasMaturity(?a,?b)
Fab Utilization	Fab(?a) ^ Utilization(?b) ^ hasUtilization(?a,?b)
Fabricated Items Per Day	FabricatedItemsPerDay(?a)
Fabricated Items Per Time	FabricatedItemsPerTime(?a)
FF	FF(?a)
GR	GR(?a)
Little's Law	LittlesLaw(?a)

Raw Term	FOL Transformed Term
Lot Prioritizations	LotPrioritization(?a)
Material Flow	MaterialFlow(?a)
Material Flow Variance	MaterialFlow(?a) ^ Variance(?b) ^ hasVariance(?a,?b)
Maximum Wait Time For Batches	WaitTime(?b) ^ Maximum(?a) ^ hasMaximum(?b,?a)
Percentage Of Bottleneck Equipment	Equipment(?b) ^ Bottleneck(?b) ^ Percentage(?a) ^ hasPercentage(?b,?a)
PS Availability	PS(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
Quality Of Planning Procedures	PlanningProcedure(?b) ^ Quality(?a) ^ hasQuality(?b,?a)
Rest 3M Availability	Rest3M(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
Risk Of Product Line Down	Product(?a) ^ LineDown(?b) ^ hasLineDown(?a,?b) ^ Risk(?c) ^ hasRisk(?b,?c)
SCM Order Patterns Variance	SCMOrderPattern(?b) ^ Variance(?a) ^ hasVariance(?b,?a)
Transportation Variability	Transportation(?a) ^ Variability(?b) ^ hasVariability(?a,?b)
Utilization Profile Variance	UtilizationProfile(?a) ^ Variance(?b) ^ hasVariance(?a,?b)
Wait Time	WaitTime(?a)
WIP	WIP(?a)
WIP Availability	WIP(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
WIP Variance	WIP(?a) ^ Variance(?b) ^ hasVariance(?a,?b)
WSPW	WSPW(?a)
WSPW Variance	WSPW(?a) ^ Variance(?b) ^ hasVariance(?a,?b)
Yearly WIP Reductions	WIP(?a) ^ Yearly(?b) ^ hasReductionFrequency(?a,?b)

Table 7-9 lists the terms and their FOL transformation that are related to machine-oriented aspects of a SI PS.

Table 7-9: Machine-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
Alpha Tool	Tool(?b) ^ Alpha(?a) ^ hasAlpha(?b,?a)
Degree Of Automation	Automation(?b) ^ Degree(?a) ^ hasDegree(?b,?a)
Degree Of Evenness Of Distribution Of Equipment Downtimes	Downtime(?d) ^ Evenness(?b) ^ hasEvenness(?d,?b) ^ Distribution(?c) ^ hasDistribution(?b,?c) ^ Degree(?a) ^ hasDegree(?c,?a)
Degree Of Exhausting Wear Limits	MachineComponent(?a) ^ WearLimit(?b) ^ hasWearLimit(?a,?b) ^ Degree(?c) ^ hasDegree(?d,?c) ^ Exhausting(?d) ^ hasExhausting(?b,?d)
Degree Of Machine-Related Process Failures	ProcessFailure(?a) ^ Machine-Related(?a) ^ Degree(?b) ^ hasDegree(?a,?b)
Engineering Time Duration	EngineeringTime(?a) ^ Duration(?b) ^ hasDuration(?a,?b)
Equipment Availability	Equipment(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
Equipment Capacity	Equipment(?a) ^ Capacity(?b) ^ hasCapacity(?a,?b)
Equipment Downtime Duration	Equipment(?a) ^ Downtime(?b) ^ hasDowntime(?a,?b) ^ Duration(?c) ^ hasDuration(?b,?c)
Equipment Downtime Frequency	Equipment(?a) ^ Downtime(?b) ^ hasDowntime(?a,?b) ^ Frequency(?c) ^ hasFrequency(?b,?c)
Equipment GR	EquipmentGR(?a)
Equipment Lifespan	Equipment(?a) ^ Lifespan(?b) ^ hasLifespan(?a,?b)
Equipment Reservations	Equipment(?a) ^ Reservation(?b) ^ hasReservation(?a,?b) ^ Percentage(?c) ^ hasPercentage(?b,?c)
Equipment Uptime	Equipment(?a) ^ Uptime(?b) ^ hasUptime(?a,?b)
Equipment Utilization	Equipment(?a) ^ Utilization(?b) ^ hasUtilization(?a,?b)
Importance Of Equipment Availability	Equipment(?b) ^ Availability(?c) ^ hasAvailability(?b,?c) ^ Importance(?a) ^ hasImportance(?c,?a)
MTBA	MTBA(?a)
MTBF	MTBF(?a)
MTBO	MTBO(?a)
MTOL	MTOL(?a)
MTTF	MTTF(?a)
MTTR	MTTR(?a)
Number Of Assists	Assist(?b) ^ Number(?a) ^ hasNumber(?b,?a)
Number Of Failures	Failure(?b) ^ Number(?a) ^ hasNumber(?b,?a)

Raw Term	FOL Transformed Term
OEE	OEE(?a)
Percentage Of New Equipment Invests	Equipment(?b) ^ NewInvest(?b) ^ Percentage(?a) ^ hasPercentage(?b,?a)
Percentage Of Process Development At Production Equipment	ProcessDevelopment(?a) ^ Equipment(?b) ^ hasUser(?b,?a) ^ Percentage(?d) ^ Manufacturing(?c) ^ hasOwner(?b,?c) ^ hasPercentage(?a, ?d)
Probability To Avoid Collateral Damages	Prevention(?b) ^ CollateralDamage(?a) ^ hasPrevention(?a,?b) ^ Probability(?c) ^ hasProbability(?b,?c)
Probability To Avoid Failures	Failure(?a) ^ Prevention(?b) ^ hasPrevention(?a,?b) ^ Probability(?c) ^ hasProbability(?b,?c)
Probability To Avoid Late Effects	LateEffect(?a) ^ Prevention(?b) ^ hasPrevention(?a,?b) ^ Probability(?c) ^ hasProbability(?b,?c)
Probability To Avoid Machine Downtimes	Machine(?a) ^ Downtime(?c) ^ hasDowntime(?a,?c) ^ Prevention(?d) ^ hasPrevention(?c,?d) ^ Probability(?b) ^ hasProbability(?d,?b)
Probability To Avoid Total Failures	Total(?a) ^ Failure(?a) ^ Prevention(?b) ^ hasPrevention(?a,?b) ^ Probability(?c) ^ hasProbability(?b,?c)
Probability To Find New Failure Patterns	Pattern(?b) ^ Failure(?a) ^ Pattern(?b) ^ hasPattern(?a,?b) ^ New(?b) ^ Discoverability(?c) ^ hasDiscoverability(?b,?c) ^ Probability(?d) ^ hasProbability(?c,?d)
Risk Of Equipment Bottleneck	Equipment(?b) ^ Bottleneck(?b) ^ Risk(?a) ^ hasRisk(?b,?a)
Scheduled Down Duration	ScheduledDown(?a) ^ Duration(?b) ^ hasDuration(?a,?b)
Scheduled Down Frequency	ScheduledDown(?a) ^ Frequency(?b) ^ hasFrequency(?a,?b)
Scheduled Down Percentage	ScheduledDown(?a) ^ Percentage(?b) ^ hasPercentage(?a,?b)
Setup Frequency	Setup(?a) ^ Frequency(?b) ^ hasFrequency(?a,?b)
Standby Time Duration	StandbyTime(?a) ^ Duration(?b) ^ hasDuration(?a,?b)
Unscheduled Down Duration	UnscheduledDown(?a) ^ Duration(?b) ^ hasDuration(?a,?b)
Unscheduled Down Frequency	UnscheduledDown(?a) ^ Frequency(?b) ^ hasFrequency(?a,?b)

Table 7-10 lists the terms and their FOL transformation that are related to operation-oriented aspects of a SI PS.

Table 7-10: Operation-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
Batch Size	BatchSize(?a)
Degree Of Tool Dedication	ToolDedication(?b) ^ Degree(?a) ^ hasDegree(?b,?a)
Number Of Wafers To Rework	Rework(?a) ^ Number(?b) ^ hasNumber(?a,?b)
Number Of Wafers To Scrap	Scrap(?b) ^ Percentage(?a) ^ hasPercentage(?b,?a)
OE	OE(?a)
Percentage Of Process Inspections	Process(?a) ^ Inspection(?b) ^ hasInspection(?a,?b) ^ Percentage(?c) ^ hasPercentage(?b,?c)
Percentage Of Rework	Rework(?b) ^ Percentage(?a) ^ hasPercentage(?b,?a)
Process Availability	Process(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
Process Maturity	Process(?a) ^ Maturity(?b) ^ hasMaturity(?a,?b)
Process Stability	Process(?a) ^ Stability(?b) ^ hasStability(?a,?b)
Process Variety	Process(?a) ^ Variety(?b) ^ hasVariety(?a,?b)
Processing Time Variance	ProcessingTime(?a) ^ Variance(?b) ^ hasVariance(?a,?b)
QE	QE(?a)
Raw Process Time	RawProcessTime(?a)
RE	RE(?a)
Scrap	Scrap(?a)
Single Process Variety	SingleProcess(?a) ^ Variety(?b) ^ hasVariety(?a,?b)

Table 7-11 lists the terms and their FOL transformation that are related to EM-oriented aspects of a SI PS.

Table 7-11: EM-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
Dependency On Algorithm Quality	Algorithm(?b) ^ Quality(?c) ^ hasQuality(?b,?c) ^ Dependency(?a) ^ hasDependency(?c,?a)
Dependency On EM Processes	EMProcess(?b) ^ Dependency(?a) ^ hasDependency(?b,?a)
Dependency On Existing Knowledge	ExistingKnowledge(?b) ^ Dependency(?a) ^ hasDependency(?b,?a)
Efficiency In Coordination Of Maintenance Process	EMProcess(?c) ^ Coordination(?b) ^ hasCoordination(?c,?b) ^ Efficiency(?a) ^ hasEfficiency(?b,?a)
Efficiency Of Spare Part Logistics	SparePartLogistics(?b) ^ Efficiency(?a) ^ hasEfficiency(?b,?a)
Efforts To Prepare Data And Algorithm	PrepareDataAndAlgorithm(?b) ^ Effort(?a) ^ hasEffort(?b,?a)
EM Availability	EM(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
EM Qualification Level	EM(?a) ^ QualificationLevel(?b) ^ hasQualificationLevel(?a,?b)
Importance Of EM Availability	EM(?b) ^ Availability(?c) ^ hasAvailability(?b,?c) ^ Importance(?a) ^ hasImportance(?c,?a)
Independency In Running Analyses	Analysis(?b) ^ Independency(?a) ^ hasIndependency(?b,?a)
Level Of Understanding Historical Failure Patterns	Failure(?a) ^ Pattern(?b) ^ hasPattern(?a,?b) ^ Historical(?b) ^ Understanding(?d) ^ hasUnderstanding(?b,?d) ^ Level(?e) ^ hasLevel(?d,?e)
Maturity Of EM Strategy	EMStrategy(?b) ^ Maturity(?a) ^ hasMaturity(?b,?a)
Number Of EM Persons Per Shift	EMStaff(?b) ^ OnShift(?b) ^ Number(?a) ^ hasNumber(?b,?a)
Offline PdM Application	PdM(?a) ^ PAApplication(?a) ^ Offline(?a)
Online PdM Application	PdM(?a) ^ PAApplication(?a) ^ Online(?a)
Percentage Of Preventive Maintenance	PreventiveMaintenance(?b) ^ Percentage(?a) ^ hasPercentage(?b,?a)
Percentage Of Reactive Maintenance	ReactiveMaintenance(?b) ^ Percentage(?a) ^ hasPercentage(?b,?a)
PdM Application	PdM(?a) ^ PAApplication(?a)
Quality Of Monitoring	Monitoring(?b) ^ Quality(?a) ^ hasQuality(?b,?a)
Quality Of Statistics	Statistics(?b) ^ Quality(?a) ^ hasQuality(?b,?a)
Repair Time	RepairTime(?a)
Speed Of Analysis	Analysis(?b) ^ Speed(?a) ^ hasSpeed(?b,?a)
Speed Of Reactions	Reaction(?b) ^ Speed(?a) ^ hasSpeed(?b,?a)
Synchronicity Of EM Availability	EM(?b) ^ Availability(?c) ^ hasAvailability(?b,?c) ^ Synchronicity(?a) ^ hasSynchronicity(?c,?a)
Transparency In Effectiveness Of EM Activities	EMActivity(?c) ^ Effectiveness(?b) ^ hasEffectiveness(?c,?b) ^ Transparency(?a) ^ hasTransparency(?b,?a)

Table 7-12 lists the terms and their FOL transformation that are related to EM-oriented aspects of a SI PS.

Table 7-12: Production Staff-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
Degree Of Operator Qualification Level	Operator(?b) ^ QualificationLevel(?c) ^ hasQualificationLevel(?b,?c) ^ Degree(?a) ^ hasDegree(?c,?a)
Degree Of Production Staff Motivation	ProductionStaff(?c) ^ Motivation(?b) ^ hasMotivation(?c,?b) ^ Degree(?a) ^ hasDegree(?b,?a)
Flexibility Of Operator Qualification Level	Operator(?b) ^ QualificationLevel(?c) ^ hasQualificationLevel(?b,?c) ^ Flexibility(?a) ^ hasFlexibility(?c,?a)
Importance Of Operator Qualification Level	Operator(?b) ^ QualificationLevel(?c) ^ hasQualificationLevel(?b,?c) ^ Importance(?a) ^ hasImportance(?c,?a)
Operator Availability	Operator(?a) ^ Availability(?b) ^ hasAvailability(?a,?b)
Operator Qualification Level	Operator(?a) ^ QualificationLevel(?b) ^ hasQualificationLevel(?a,?b)

Table 7-13 lists the terms and their FOL transformation that are related to EM-oriented aspects of a SI PS.

Table 7-13: Cost-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
EM Costs	EM(?a) ^ Costs(?b) ^ hasCosts(?a,?b)
Inventory Costs	Inventory(?a) ^ Costs(?b) ^ hasCosts(?a,?b)
Personnel Costs	Personnel(?a) ^ Costs(?b) ^ hasCosts(?a,?b)
Product Costs	Product(?a) ^ Costs(?b) ^ hasCosts(?a,?b)
Spare Part Costs	SparePart(?a) ^ Costs(?b) ^ hasCosts(?a,?b)

Table 7-14 lists the terms and their FOL transformation that are related to data-oriented aspects of a SI PS.

Table 7-14: Data-oriented Terms and FOL Transformation

Raw Term	FOL Transformed Term
Data Traffic	DataTraffic(?a)
Number Of Relevant Data Sources	RelevantDataSource(?b) ^ Number(?a) ^ hasNumber(?b,?a)

To ensure a consistent rule model, it is important to differentiate the variables clearly. Since each rule represents the logical association between two terms, the variables are separated by the postfix ‘1’ and ‘2’. This postfix allows human analysts to clearly see which concept and object property belongs together as a term. A term itself may consist of multiple logical associations to express the original meaning in a logical and atomic standard. If such complex terms are set in a relationship within a FOL rule, it is required to select the correct pair of variables. The following sample FOL rule demonstrates the problem:

MachineComponent(?a1) ^ WearLimit(?b1) ^ hasWearLimit(?a1,?b1) ^ Degree(?c1) ^ hasDegree(?d1,?c1) ^ Exhausting(?d1) ^ hasExhausting(?b1,?d1) ^ EM(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?c1, ?b2)

The first term is expressed by four concepts and two object properties that use four variables a1, b1, c1 and d1. The second term is simpler and consists of only two concepts and one object property, which use two variables a2 and b2. From the case study evaluation, it is known that the first term decreases the second term. In FOL language, the particular interfering variables from both terms must be identified. In this case, the variable c1 that represents a certain ‘Degree’ will decrease the variable b2 that represents

‘Costs’. Based on the case study association matrix, 272 FOL rules need to be created, accordingly. Each rule must be verified to ensure the correct pair of variables. To present the list of rules in a clear way, the list is divided by those classes that were assigned to the source term of each rule. Table 7-15 shows the PS-oriented SWRL rules for PPES.

Table 7-15: PS-oriented SWRL Rules for PPES

#	Rule
1	4M(?a1) ^ Synchronicity(?b1) ^ hasSynchronicity(?a1,?b1) ^ CT(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?b1, ?b2)
2	4M(?a1) ^ Synchronicity(?b1) ^ hasSynchronicity(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
3	CT(?a1) ^ FF(?a2) → increase(?a1, ?a2)
4	CT(?a1) ^ LittlesLaw(?a2) → increase(?a1, ?a2)
5	CT(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
6	Dispatcher(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ 4M(?a2) ^ Synchronicity(?b2) ^ hasSynchronicity(?a2,?b2) → increase(?b1, ?b2)
7	Dispatcher(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
8	DispatcherCompliance(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ FF(?a2) → decrease(?a1, ?a2)
9	DispatcherCompliance(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?a1, ?b2)
10	DispatcherCompliance(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?a1, ?b2)
11	Engineer(?c1) ^ Knowledge(?a1) ^ hasKnowledge(?c1,?a1) ^ FactoryPhysics(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ MaterialFlow(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?b1, ?b2)
12	Equipment(?b1) ^ Bottleneck(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ CT(?a2) → increase(?a1, ?a2)
13	Equipment(?b1) ^ Bottleneck(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ FF(?a2) → increase(?a1, ?a2)
14	Equipment(?b1) ^ Bottleneck(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ GR(?a2) → decrease(?a1, ?a2)
15	Equipment(?b1) ^ Bottleneck(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ WIP(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
16	EquipmentGR (?a1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?a1, ?b2)
17	Fab(?a1) ^ Utilization(?b1) ^ hasUtilization(?a1,?b1) ^ Equipment(?a2) ^ Downtime(?b2) ^ hasDowntime(?a2,?b2) ^ Frequency(?c2) ^ hasFrequency(?b2,?c2) → increase(?b1, ?c2)
18	Fab(?a1) ^ Utilization(?b1) ^ hasUtilization(?a1,?b1) ^ ScheduledDown(?a2) ^ Percentage(?b2) ^ hasPercentage(?a2,?b2) → increase(?b1, ?b2)
19	FabricatedItemsPerDay(?a1) ^ DGR(?a2) → increase(?a1, ?a2)
20	FabricatedItemsPerDay(?a1) ^ PS(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?a1, ?b2)
21	FabricatedItemsPerTime(?a1) ^ GR(?a2) → increase(?a1, ?a2)
22	GR(?a1) ^ CT(?a2) → decrease(?a1, ?a2)
23	GR(?a1) ^ DGR(?a2) → increase(?a1, ?a2)
24	GR(?a1) ^ Equipment(?a2) ^ Utilization(?b2) ^ hasUtilization(?a2,?b2) → increase(?a1, ?b2)
25	GR(?a1) ^ GR(?a2) → increase(?a1, ?a2)
26	GR(?a1) ^ LittlesLaw(?a2) → increase(?a1, ?a2)
27	GR(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?a1, ?a2)
28	GR(?a1) ^ WIP(?a2) → decrease(?a1, ?a2)
29	GR(?a1) ^ WSPW(?a2) → increase(?a1, ?a2)
30	LotPrioritization(?a1) ^ CT(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?a1, ?b2)
31	LotPrioritization(?a1) ^ GR(?a2) → decrease(?a1, ?a2)
32	MachineGroup(?b1) ^ PerformanceSynchronicity(?a1) ^ hasPerformanceSynchronicity(?b1,?a1) ^ Degree(?c1) ^ hasDegree(?a1,?c1) ^ FF(?a2) → decrease(?c1, ?a2)

#	Rule
33	MaterialFlow(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ CT(?a2) → increase(?b1, ?a2)
34	MaterialFlow(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → decrease(?b1, ?b2)
35	MaterialFlow(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ FF(?a2) → increase(?b1, ?a2)
36	MaterialFlow(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ GR(?a2) → decrease(?b1, ?a2)
37	MaterialFlow(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?b1, ?a2)
38	MaterialFlow(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ WIP(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?b1, ?a2)
39	Rest3M(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
40	SCMOrderPattern(?b1) ^ Variance(?a1) ^ hasVariance(?b1,?a1) ^ WSPW(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?a1, ?b2)
41	Transportation(?a1) ^ Variability(?b1) ^ hasVariability(?a1,?b1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → decrease(?b1, ?b2)
42	UtilizationProfile(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ CT(?a2) → increase(?b1, ?a2)
43	UtilizationProfile(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ Equipment(?b2) ^ Bottleneck(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → increase(?b1, ?a2)
44	WaitTime(?a1) ^ CT(?a2) → increase(?a1, ?a2)
45	WaitTime(?b1) ^ Maximum(?a1) ^ hasMaximum(?b1,?a1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?a1, ?b2)
46	WIP(?a1) ^ CT(?a2) → increase(?a1, ?a2)
47	WIP(?a1) ^ FF(?a2) → increase(?a1, ?a2)
48	WIP(?a1) ^ LittlesLaw(?a2) → increase(?a1, ?a2)
49	WIP(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
50	WIP(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ DGR(?a2) → increase(?b1, ?a2)
51	WIP(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ PS(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
52	WIP(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ CT(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?b1, ?b2)
53	WIP(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ FF(?a2) → increase(?b1, ?a2)
54	WIP(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?b1, ?b2)
55	WIP(?a1) ^ Yearly(?b1) ^ hasReductionFrequency(?a1,?b1) ^ WSPW(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?b1, ?b2)
56	WIPDistribution(?c1) ^ Unevenness(?b1) ^ hasUnevenness(?c1,?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ GR(?a2) → decrease(?a1, ?a2)
57	WSPW(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ Equipment(?b2) ^ Bottleneck(?b2) ^ Risk(?a2) ^ hasRisk(?b2,?a2) → increase(?b1, ?a2)
58	WSPW(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ FF(?a2) → increase(?b1, ?a2)
59	WSPW(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?b1, ?b2)
60	WSPW(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?b1, ?b2)

Table 7-16 shows the SWRL rules for PPES whose source terms are classified as machine-oriented.

Table 7-16: Machine-oriented SWRL Rules for PPES

#	Rule
1	Assist(?b1) ^ Number(?a1) ^ hasNumber(?b1,?a1) ^ MTBA(?a2) → decrease(?a1, ?a2)
2	Automation(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ Operator(?a2) ^ QualificationLevel(?b2) ^ hasQualificationLevel(?a2,?b2) → decrease(?a1, ?b2)
3	Automation(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ Operator(?b2) ^ QualificationLevel(?c2) ^ hasQualificationLevel(?b2,?c2) ^ Importance(?a2) ^ hasImportance(?c2,?a2) → decrease(?a1, ?a2)
4	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ DGR(?a2) → increase(?b1, ?a2)

#	Rule
5	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → increase(?b1, ?b2)
6	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ FF(?a2) → decrease(?b1, ?a2)
7	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ GR(?a2) → increase(?b1, ?a2)
8	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ OEE(?a2) → increase(?b1, ?a2)
9	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ PS(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
10	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?b1, ?a2)
11	Equipment(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?b1, ?b2)
12	Equipment(?a1) ^ Capacity(?b1) ^ hasCapacity(?a1,?b1) ^ Equipment(?a2) ^ Utilization(?b2) ^ hasUtilization(?a2,?b2) → decrease(?b1, ?b2)
13	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ CT(?a2) → increase(?c1, ?a2)
14	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → decrease(?c1, ?b2)
15	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ FF(?a2) → increase(?c1, ?a2)
16	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ GR(?a2) → decrease(?c1, ?a2)
17	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ MTBF(?a2) → decrease(?c1, ?a2)
18	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ MTOL(?a2) → increase(?c1, ?a2)
19	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ MTTR(?a2) → increase(?c1, ?a2)
20	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ OEE(?a2) → decrease(?c1, ?a2)
21	Equipment(?a1) ^ Downtime(?b1) ^ hasDowntime(?a1,?b1) ^ Duration(?c1) ^ hasDuration(?b1,?c1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?c1, ?a2)
22	Equipment(?a1) ^ Reservation(?b1) ^ hasReservation(?a1,?b1) ^ Percentage(?c1) ^ hasPercentage(?b1,?c1) ^ EngineeringTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?c1, ?b2)
23	Equipment(?a1) ^ Reservation(?b1) ^ hasReservation(?a1,?b1) ^ Percentage(?c1) ^ hasPercentage(?b1,?c1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → decrease(?c1, ?b2)
24	Equipment(?a1) ^ Reservation(?b1) ^ hasReservation(?a1,?b1) ^ Percentage(?c1) ^ hasPercentage(?b1,?c1) ^ FF(?a2) → increase(?c1, ?a2)
25	Equipment(?a1) ^ Reservation(?b1) ^ hasReservation(?a1,?b1) ^ Percentage(?c1) ^ hasPercentage(?b1,?c1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?c1, ?b2)
26	Equipment(?a1) ^ Reservation(?b1) ^ hasReservation(?a1,?b1) ^ Percentage(?c1) ^ hasPercentage(?b1,?c1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?c1, ?b2)
27	EquipmentGR(?a1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → increase(?a1, ?b2)
28	EquipmentGR(?a1) ^ GR(?a2) → increase(?a1, ?a2)
29	Failure(?b1) ^ Number(?a1) ^ hasNumber(?b1,?a1) ^ MTBF(?a2) → decrease(?a1, ?a2)
30	Failure(?b1) ^ Number(?a1) ^ hasNumber(?b1,?a1) ^ MTOL(?a2) → decrease(?a1, ?a2)
31	Failure(?b1) ^ Number(?a1) ^ hasNumber(?b1,?a1) ^ MTTF(?a2) → decrease(?a1, ?a2)
32	Failure(?b1) ^ Number(?a1) ^ hasNumber(?b1,?a1) ^ MTTR(?a2) → decrease(?a1, ?a2)
33	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ CT(?a2) → decrease(?b1, ?a2)
34	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
35	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ FF(?a2) → decrease(?b1, ?a2)

#	Rule
36	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ GR(?a2) → increase(?b1, ?a2)
37	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ MTBF(?a2) → increase(?b1, ?a2)
38	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ MTOL(?a2) → decrease(?b1, ?a2)
39	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ MTTR(?a2) → decrease(?b1, ?a2)
40	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ OEE(?a2) → increase(?b1, ?a2)
41	Machine(?a1) ^ Downtime(?c1) ^ hasDowntime(?a1,?c1) ^ Prevention(?d1) ^ hasPrevention(?c1,?d1) ^ Probability(?b1) ^ hasProbability(?d1,?b1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?b1, ?a2)
42	MachineComponent(?a1) ^ WearLimit(?b1) ^ hasWearLimit(?a1,?b1) ^ Degree(?c1) ^ hasDegree(?d1,?c1) ^ Exhausting(?d1) ^ hasExhausting(?b1,?d1) ^ EM(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?c1, ?b2)
43	MachineComponent(?a1) ^ WearLimit(?b1) ^ hasWearLimit(?a1,?b1) ^ Degree(?c1) ^ hasDegree(?d1,?c1) ^ Exhausting(?d1) ^ hasExhausting(?b1,?d1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?c1, ?b2)
44	MachineComponent(?a1) ^ WearLimit(?b1) ^ hasWearLimit(?a1,?b1) ^ Degree(?c1) ^ hasDegree(?d1,?c1) ^ Exhausting(?d1) ^ hasExhausting(?b1,?d1) ^ MTBF(?a2) → increase(?c1, ?a2)
45	MachineComponent(?a1) ^ WearLimit(?b1) ^ hasWearLimit(?a1,?b1) ^ Degree(?c1) ^ hasDegree(?d1,?c1) ^ Exhausting(?d1) ^ hasExhausting(?b1,?d1) ^ SparePart(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?c1, ?b2)
46	MTBA(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?a1, ?a2)
47	MTBF(?a1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?a1, ?b2)
48	MTBF(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?a1, ?a2)
49	MTOL(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
50	MTOL(?a1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
51	MTTR(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
52	OEE(?a1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → increase(?a1, ?b2)
53	OEE(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?a1, ?a2)
54	ProcessDevelopment(?a1) ^ Equipment(?b1) ^ hasUser(?b1,?a1) ^ Percentage(?d1) ^ Manufacturing(?c1) ^ hasOwner(?b1,?c1) ^ hasPercentage(?a1, ?d1) ^ CT(?a2) → increase(?d1, ?a2)
55	ProcessDevelopment(?a1) ^ Equipment(?b1) ^ hasUser(?b1,?a1) ^ Percentage(?d1) ^ Manufacturing(?c1) ^ hasOwner(?b1,?c1) ^ hasPercentage(?a1, ?d1) ^ EngineeringTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?d1, ?b2)
56	ProcessDevelopment(?a1) ^ Equipment(?b1) ^ hasUser(?b1,?a1) ^ Percentage(?d1) ^ Manufacturing(?c1) ^ hasOwner(?b1,?c1) ^ hasPercentage(?a1, ?d1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → decrease(?d1, ?b2)
57	ProcessDevelopment(?a1) ^ Equipment(?b1) ^ hasUser(?b1,?a1) ^ Percentage(?d1) ^ Manufacturing(?c1) ^ hasOwner(?b1,?c1) ^ hasPercentage(?a1, ?d1) ^ GR(?a2) → decrease(?d1, ?a2)
58	ProcessDevelopment(?a1) ^ Equipment(?b1) ^ hasUser(?b1,?a1) ^ Percentage(?d1) ^ Manufacturing(?c1) ^ hasOwner(?b1,?c1) ^ hasPercentage(?a1, ?d1) ^ UnscheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → increase(?d1, ?b2)
59	ProcessFailure(?a1) ^ Machine-Related(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ CT(?a2) → increase(?b1, ?a2)
60	ProcessFailure(?a1) ^ Machine-Related(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ GR(?a2) → decrease(?b1, ?a2)
61	ProcessFailure(?a1) ^ Machine-Related(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ Product(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → increase(?b1, ?b2)
62	ProcessFailure(?a1) ^ Machine-Related(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ Rework(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → increase(?b1, ?a2)
63	ProcessFailure(?a1) ^ Machine-Related(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ Scrap(?a2) → increase(?b1, ?a2)
64	ProcessFailure(?a1) ^ Machine-Related(?a1) ^ Degree(?b1) ^ hasDegree(?a1,?b1) ^ Yield(?a2) → decrease(?b1, ?a2)

#	Rule
65	ScheduledDown(?a1) ^ Frequency(?b1) ^ hasFrequency(?a1,?b1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?b1, ?a2)
66	Setup(?a1) ^ Frequency(?b1) ^ hasFrequency(?a1,?b1) ^ EM(?b2) ^ Availability(?c2) ^ hasAvailability(?b2,?c2) ^ Importance(?a2) ^ hasImportance(?c2,?a2) → increase(?b1, ?a2)
67	Setup(?a1) ^ Frequency(?b1) ^ hasFrequency(?a1,?b1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → decrease(?b1, ?b2)
68	Setup(?a1) ^ Frequency(?b1) ^ hasFrequency(?a1,?b1) ^ ScheduledDown(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → increase(?b1, ?b2)
69	Tool(?b1) ^ Alpha(?a1) ^ hasAlpha(?b1,?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)

Table 7-17 shows the SWRL rules for PPES whose source terms are classified as operation-oriented.

Table 7-17: Operation-oriented SWRL Rules for PPES

#	Rule
1	BatchSize(?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
2	OE(?a1) ^ OEE(?a2) → increase(?a1, ?a2)
3	Process(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ DGR(?a2) → increase(?b1, ?a2)
4	Process(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → increase(?b1, ?b2)
5	Process(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ GR(?a2) → increase(?b1, ?a2)
6	Process(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ PS(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
7	Process(?a1) ^ Inspection(?b1) ^ hasInspection(?a1,?b1) ^ Percentage(?c1) ^ hasPercentage(?b1,?c1) ^ CT(?a2) → increase(?c1, ?a2)
8	Process(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
9	Process(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ Process(?a2) ^ Stability(?b2) ^ hasStability(?a2,?b2) → increase(?b1, ?b2)
10	Process(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ Rest3M(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
11	Process(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
12	Process(?a1) ^ Maturity(?b1) ^ hasMaturity(?a1,?b1) ^ UnscheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → decrease(?b1, ?b2)
13	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ Automation(?b2) ^ Degree(?a2) ^ hasDegree(?b2,?a2) → increase(?b1, ?a2)
14	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ CT(?a2) → decrease(?b1, ?a2)
15	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
16	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ FF(?a2) → decrease(?b1, ?a2)
17	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ Process(?a2) ^ Inspection(?b2) ^ hasInspection(?a2,?b2) ^ Percentage(?c2) ^ hasPercentage(?b2,?c2) → decrease(?b1, ?c2)
18	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
19	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ UnscheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → decrease(?b1, ?b2)
20	Process(?a1) ^ Stability(?b1) ^ hasStability(?a1,?b1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?b1, ?b2)
21	Process(?a1) ^ Variety(?b1) ^ hasVariety(?a1,?b1) ^ ScheduledDown(?a2) ^ Percentage(?b2) ^ hasPercentage(?a2,?b2) → increase(?b1, ?b2)
22	ProcessingTime(?a1) ^ Variance(?b1) ^ hasVariance(?a1,?b1) ^ FF(?a2) → increase(?b1, ?a2)
23	QE(?a1) ^ OEE(?a2) → increase(?a1, ?a2)
24	RawProcessTime(?a1) ^ FF(?a2) → decrease(?a1, ?a2)
25	RawProcessTime(?a1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?a1, ?a2)

#	Rule
26	RE(?a1) ^ GR(?a2) → increase(?a1, ?a2)
27	RE(?a1) ^ OEE(?a2) → increase(?a1, ?a2)
28	Rework(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ GR(?a2) → decrease(?a1, ?a2)
29	Scrap(?b1) ^ Number(?a1) ^ hasNumber(?b1,?a1) ^ QE(?a2) → decrease(?a1, ?a2)
30	SingleProcess(?a1) ^ Variety(?b1) ^ hasVariety(?a1,?b1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → decrease(?b1, ?b2)
31	SingleProcess(?a1) ^ Variety(?b1) ^ hasVariety(?a1,?b1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?b1, ?a2)
32	SingleProcess(?a1) ^ Variety(?b1) ^ hasVariety(?a1,?b1) ^ Setup(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → increase(?b1, ?b2)
33	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ CT(?a2) → increase(?a1, ?a2)
34	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ Deliverability(?a2) → decrease(?a1, ?a2)
35	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ Equipment(?a2) ^ Capacity(?b2) ^ hasCapacity(?a2,?b2) → decrease(?a1, ?b2)
36	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ Equipment(?b2) ^ Availability(?c2) ^ hasAvailability(?b2,?c2) ^ Importance(?a2) ^ hasImportance(?c2,?a2) → increase(?a1, ?a2)
37	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ FF(?a2) → increase(?a1, ?a2)
38	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ MaterialFlow(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?a1, ?b2)
39	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ Product(?a2) ^ LineDown(?b2) ^ hasLineDown(?a2,?b2) ^ Risk(?c2) ^ hasRisk(?b2,?c2) → increase(?a1, ?c2)
40	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ PS(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → increase(?a1, ?a2)
41	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?a1, ?b2)
42	ToolDedication(?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → increase(?a1, ?b2)
43	Rework(?a1) ^ Number(?b1) ^ hasNumber(?a1,?b1) ^ QE(?a2) → decrease(?b1, ?a2)

Table 7-18 shows the SWRL rules for PPES whose source terms are classified as EM-oriented.

Table 7-18: EM-oriented SWRL Rules for PPES

#	Rule
1	EM(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
2	EM(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
3	EM(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ UnscheduledDown(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
4	EM(?a1) ^ QualificationLevel(?b1) ^ hasQualificationLevel(?a1,?b1) ^ ScheduledDown(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
5	EM(?a1) ^ QualificationLevel(?b1) ^ hasQualificationLevel(?a1,?b1) ^ UnscheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → decrease(?b1, ?b2)
6	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ EM(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?a1, ?b2)
7	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?a1, ?b2)
8	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ FF(?a2) → decrease(?a1, ?a2)
9	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ MTBF(?a2) → increase(?a1, ?a2)

#	Rule
10	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ MTOL(?a2) → decrease(?a1, ?a2)
11	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ MTTR(?a2) → decrease(?a1, ?a2)
12	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ Personnel(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?a1, ?b2)
13	EMProcess(?c1) ^ Coordination(?b1) ^ hasCoordination(?c1,?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ QE(?a2) → increase(?a1, ?a2)
14	EMStrategy(?b1) ^ Maturity(?a1) ^ hasMaturity(?b1,?a1) ^ EquipmentGR(?a2) → increase(?a1, ?a2)
15	PdM(?a1) ^ Application(?a1) ^ Offline(?a1) ^Failure(?a2) ^ Pattern(?b2) ^ hasPattern(?a2,?b2) ^ Historical(?b2) ^ Understanding(?d2) ^ hasUnderstanding(?b2,?d2) ^ Level(?e2) ^ hasLevel(?d2,?e2) → increase(?a1, ?e2)
16	PdM(?a1) ^ PAApplication(?a1) ^ CT(?a2) → decrease(?a1, ?a2)
17	PdM(?a1) ^ PAApplication(?a1) ^ EM(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?a1, ?b2)
18	PdM(?a1) ^ PAApplication(?a1) ^ EM(?b2) ^ Availability(?c2) ^ hasAvailability(?b2,?c2) ^ Synchronicity(?a2) ^ hasSynchronicity(?c2,?a2) → increase(?a1, ?a2)
19	PdM(?a1) ^ PAApplication(?a1) ^ EMProcess(?c2) ^ Coordination(?b2) ^ hasCoordination(?c2,?b2) ^ Efficiency(?a2) ^ hasEfficiency(?b2,?a2) → increase(?a1, ?a2)
20	PdM(?a1) ^ PAApplication(?a1) ^ Equipment(?a2) ^ Downtime(?b2) ^ hasDowntime(?a2,?b2) ^ Duration(?c2) ^ hasDuration(?b2,?c2) → decrease(?a1, ?c2)
21	PdM(?a1) ^ PAApplication(?a1) ^ Equipment(?a2) ^ Uptime(?b2) ^ hasUptime(?a2,?b2) → increase(?a1, ?b2)
22	PdM(?a1) ^ PAApplication(?a1) ^ Equipment(?b2) ^ Bottleneck(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → decrease(?a1, ?a2)
23	PdM(?a1) ^ PAApplication(?a1) ^ GR(?a2) → increase(?a1, ?a2)
24	PdM(?a1) ^ PAApplication(?a1) ^ Machine(?a2) ^ Downtime(?c2) ^ hasDowntime(?a2,?c2) ^ Prevention(?d2) ^ hasPrevention(?c2,?d2) ^ Probability(?b2) ^ hasProbability(?d2,?b2) → increase(?a1, ?b2)
25	PdM(?a1) ^ PAApplication(?a1) ^ MachineComponent(?a2) ^ WearLimit(?b2) ^ hasWearLimit(?a2,?b2) ^ Degree(?c2) ^ hasDegree(?d2,?c2) ^ Exhausting(?d2) ^ hasExhausting(?b2,?d2) → increase(?a1, ?c2)
26	PdM(?a1) ^ PAApplication(?a1) ^ MaterialFlow(?a2) → increase(?a1, ?a2)
27	PdM(?a1) ^ PAApplication(?a1) ^ MaterialFlow(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?a1, ?b2)
28	PdM(?a1) ^ PAApplication(?a1) ^ MTBO(?a2) → decrease(?a1, ?a2)
29	PdM(?a1) ^ PAApplication(?a1) ^ MTOL(?a2) → decrease(?a1, ?a2)
30	PdM(?a1) ^ PAApplication(?a1) ^ ProcessFailure(?a2) ^ Machine-Related(?a2) ^ Degree(?b2) ^ hasDegree(?a2,?b2) → decrease(?a1, ?b2)
31	PdM(?a1) ^ PAApplication(?a1) ^ ProductionStaff(?c2) ^ Motivation(?b2) ^ hasMotivation(?c2,?b2) ^ Degree(?a2) ^ hasDegree(?b2,?a2) → increase(?a1, ?a2)
32	PdM(?a1) ^ PAApplication(?a1) ^ RepairTime(?a2) → decrease(?a1, ?a2)
33	PdM(?a1) ^ PAApplication(?a1) ^ ScheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → increase(?a1, ?b2)
34	PdM(?a1) ^ PAApplication(?a1) ^ SparePartLogistics(?b2) ^ Efficiency(?a2) ^ hasEfficiency(?b2,?a2) → increase(?a1, ?a2)
35	PdM(?a1) ^ PAApplication(?a1) ^ Tool(?b2) ^ Alpha(?a2) ^ hasAlpha(?b2,?a2) → decrease(?a1, ?a2)
36	PdM(?a1) ^ PAApplication(?a1) ^ UnscheduledDown(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?a1, ?b2)
37	PdM(?a1) ^ PAApplication(?a1) ^ UnscheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → decrease(?a1, ?b2)
38	PdM(?a1) ^ PAApplication(?a1) ^ WIP(?a2) → decrease(?a1, ?a2)
39	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ EMActivity(?c2) ^ Effectiveness(?b2) ^ hasEffectiveness(?c2,?b2) ^ Transparency(?a2) ^ hasTransparency(?b2,?a2) → increase(?a1, ?a2)
40	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ Monitoring(?b2) ^ Quality(?a2) ^ hasQuality(?b2,?a2) → increase(?a1, ?a2)
41	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ PlanningProcedure(?b2) ^ Quality(?a2) ^ hasQuality(?b2,?a2) → increase(?a1, ?a2)
42	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ Reaction(?b2) ^ Speed(?a2) ^ hasSpeed(?b2,?a2) → decrease(?a1, ?a2)
43	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ RelevantDataSource(?b2) ^ Number(?a2) ^ hasNumber(?b2,?a2) → increase(?a1, ?a2)

#	Rule
44	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ Statistics(?b2) ^ Quality(?a2) ^ hasQuality(?b2,?a2) → increase(?a1, ?a2)
45	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ Analysis(?b2) ^ Independency(?a2) ^ hasIndependency(?b2,?a2) → increase(?a1, ?a2)
46	PdM(?a1) ^ PAApplication(?a1) ^ Offline(?a1) ^ Pattern(?b2) ^ Failure(?a2) ^ Pattern(?b2) ^ hasPattern(?a2,?b2) ^ New(?b2) ^ Discoverability(?c2) ^ hasDiscoverability(?b2,?c2) ^ Probability(?d2) ^ hasProbability(?c2,?d2) → increase(?a1, ?d2)
47	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ Algorithm(?b2) ^ Quality(?c2) ^ hasQuality(?b2,?c2) ^ Dependency(?a2) ^ hasDependency(?c2,?a2) → increase(?a1, ?a2)
48	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ DataTraffic(?a2) → increase(?a1, ?a2)
49	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ EMProcess(?b2) ^ Dependency(?a2) ^ hasDependency(?b2,?a2) → increase(?a1, ?a2)
50	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ ExistingKnowledge(?b2) ^ Dependency(?a2) ^ hasDependency(?b2,?a2) → increase(?a1, ?a2)
51	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ PrepareDataAndAlgorithm(?b2) ^ Effort(?a2) ^ hasEffort(?b2,?a2) → increase(?a1, ?a2)
52	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ Reaction(?b2) ^ Speed(?a2) ^ hasSpeed(?b2,?a2) → increase(?a1, ?a2)
53	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ Statistics(?b2) ^ Quality(?a2) ^ hasQuality(?b2,?a2) → decrease(?a1, ?a2)
54	PdM(?a1) ^ PAApplication(?a1) ^ Online(?a1) ^ Failure(?a2) ^ Prevention(?b2) ^ hasPrevention(?a2,?b2) ^ Probability(?c2) ^ hasProbability(?b2,?c2) → increase(?a1, ?c2)
55	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Analysis(?b2) ^ Speed(?a2) ^ hasSpeed(?b2,?a2) → increase(?a1, ?a2)
56	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Equipment(?a2) ^ Downtime(?b2) ^ hasDowntime(?a2,?b2) ^ Duration(?c2) ^ hasDuration(?b2,?c2) → decrease(?a1, ?c2)
57	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ MTTR(?a2) → decrease(?a1, ?a2)
58	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ PlanningProcedure(?b2) ^ Quality(?a2) ^ hasQuality(?b2,?a2) → increase(?a1, ?a2)
59	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Reaction(?b2) ^ Speed(?a2) ^ hasSpeed(?b2,?a2) → increase(?a1, ?a2)
60	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ UnscheduledDown(?a2) ^ Frequency(?b2) ^ hasFrequency(?a2,?b2) → decrease(?a1, ?b2)
61	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ LateEffect(?a2) ^ Prevention(?b2) ^ hasPrevention(?a2,?b2) ^ Probability(?c2) ^ hasProbability(?b2,?c2) → increase(?a1, ?c2)
62	PreventiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Prevention(?b2) ^ CollateralDamage(?a2) ^ hasPrevention(?a2,?b2) ^ Probability(?c2) ^ hasProbability(?b2,?c2) → increase(?a1, ?c2)
63	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Downtime(?d2) ^ Evenness(?b2) ^ hasEvenness(?d2,?b2) ^ Distribution(?c2) ^ hasDistribution(?b2,?c2) ^ Degree(?a2) ^ hasDegree(?c2,?a2) → increase(?a1, ?a2)
64	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ EMProcess(?c2) ^ Coordination(?b2) ^ hasCoordination(?c2,?b2) ^ Efficiency(?a2) ^ hasEfficiency(?b2,?a2) → decrease(?a1, ?a2)
65	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ EMStaff(?b2) ^ OnShift(?b2) ^ Number(?a2) ^ hasNumber(?b2,?a2) → increase(?a1, ?a2)
66	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Equipment(?a2) ^ Downtime(?b2) ^ hasDowntime(?a2,?b2) ^ Duration(?c2) ^ hasDuration(?b2,?c2) → decrease(?a1, ?c2)
67	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Equipment(?a2) ^ Lifespan(?b2) ^ hasLifespan(?a2,?b2) → decrease(?a1, ?b2)
68	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Equipment(?b2) ^ NewInvest(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → increase(?a1, ?a2)
69	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ MachineComponent(?a2) ^ WearLimit(?b2) ^ hasWearLimit(?a2,?b2) ^ Degree(?c2) ^ hasDegree(?d2,?c2) ^ Exhausting(?d2) ^ hasExhausting(?b2,?d2) → decrease(?a1, ?c2)
70	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Monitoring(?b2) ^ Quality(?a2) ^ hasQuality(?b2,?a2) → decrease(?a1, ?a2)
71	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Rework(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → increase(?a1, ?a2)
72	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ SparePartLogistics(?b2) ^ Efficiency(?a2) ^ hasEfficiency(?b2,?a2) → decrease(?a1, ?a2)

#	Rule
73	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Prevention(?b2) ^ CollateralDamage(?a2) ^ hasPrevention(?a2,?b2) ^ Probability(?c2) ^ hasProbability(?b2,?c2) → decrease(?a1, ?c2)
74	ReactiveMaintenance(?b1) ^ Percentage(?a1) ^ hasPercentage(?b1,?a1) ^ Total(?a2) ^ Failure(?a2) ^ Prevention(?b2) ^ hasPrevention(?a2,?b2) ^ Probability(?c2) ^ hasProbability(?b2,?c2) → decrease(?a1, ?c2)
75	RepairTime(?a1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → decrease(?a1, ?b2)
76	RepairTime(?a1) ^ FF(?a2) → increase(?a1, ?a2)
77	RepairTime(?a1) ^ MTOL(?a2) → increase(?a1, ?a2)
78	RepairTime(?a1) ^ MTTR(?a2) → increase(?a1, ?a2)
79	SparePartLogistics(?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ EM(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?a1, ?b2)
80	SparePartLogistics(?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ Equipment(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?a1, ?b2)
81	SparePartLogistics(?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ Inventory(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?a1, ?b2)
82	SparePartLogistics(?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ MTTR(?a2) → decrease(?a1, ?a2)
83	SparePartLogistics(?b1) ^ Efficiency(?a1) ^ hasEfficiency(?b1,?a1) ^ SparePart(?a2) ^ Costs(?b2) ^ hasCosts(?a2,?b2) → decrease(?a1, ?b2)
84	PdM(?a1) ^ PreventiveMaintenance(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → increase(?a1, ?a2)
85	PdM(?a1) ^ ReactiveMaintenance(?b2) ^ Percentage(?a2) ^ hasPercentage(?b2,?a2) → decrease(?a1, ?a2)

Table 7-19 shows the SWRL rules for PPES whose source terms are classified as production staff-oriented.

Table 7-19: Production Staff-oriented SWRL Rules for PPES

#	Rule
1	Operator(?b1) ^ QualificationLevel(?c1) ^ hasQualificationLevel(?b1,?c1) ^ Degree(?a1) ^ hasDegree(?c1,?a1) ^ CT(?a2) → decrease(?a1, ?a2)
2	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ CT(?a2) → decrease(?b1, ?a2)
3	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ DGR(?a2) → increase(?b1, ?a2)
4	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ FF(?a2) → decrease(?b1, ?a2)
5	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ GR(?a2) → increase(?b1, ?a2)
6	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ PS(?a2) ^ Availability(?b2) ^ hasAvailability(?a2,?b2) → increase(?b1, ?b2)
7	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
8	Operator(?a1) ^ Availability(?b1) ^ hasAvailability(?a1,?b1) ^ WIP(?a2) ^ Variance(?b2) ^ hasVariance(?a2,?b2) → decrease(?b1, ?b2)
9	Operator(?a1) ^ QualificationLevel(?b1) ^ hasQualificationLevel(?a1,?b1) ^ FF(?a2) → decrease(?b1, ?a2)
10	Operator(?a1) ^ QualificationLevel(?b1) ^ hasQualificationLevel(?a1,?b1) ^ Operator(?b2) ^ QualificationLevel(?c2) ^ hasQualificationLevel(?b2,?c2) ^ Flexibility(?a2) ^ hasFlexibility(?c2,?a2) → increase(?b1, ?a2)
11	Operator(?a1) ^ QualificationLevel(?b1) ^ hasQualificationLevel(?a1,?b1) ^ StandbyTime(?a2) ^ Duration(?b2) ^ hasDuration(?a2,?b2) → decrease(?b1, ?b2)
12	Operator(?b1) ^ QualificationLevel(?c1) ^ hasQualificationLevel(?b1,?c1) ^ Degree(?a1) ^ hasDegree(?c1,?a1) ^ FF(?a2) → decrease(?a1, ?a2)
13	Operator(?b1) ^ QualificationLevel(?c1) ^ hasQualificationLevel(?b1,?c1) ^ Degree(?a1) ^ hasDegree(?c1,?a1) ^ GR(?a2) → increase(?a1, ?a2)
14	Operator(?b1) ^ QualificationLevel(?c1) ^ hasQualificationLevel(?b1,?c1) ^ Flexibility(?a1) ^ hasFlexibility(?c1,?a1) ^ CT(?a2) → decrease(?a1, ?a2)
15	ProductionStaff(?c1) ^ Motivation(?b1) ^ hasMotivation(?c1,?b1) ^ Degree(?a1) ^ hasDegree(?b1,?a1) ^ CT(?a2) → decrease(?a1, ?a2)

As highlighted in 7.5, additional rules are required to model the semantics of the object properties ‘increase‘ and ‘decrease‘, their logical relation and guidelines for transitivity. The Protégé reasoner needs to understand that both terms have an opposite meaning to each other. Thus, the FOL rules need to describe when a variable has a transitive impact on another variable and if this impact has a decreasing or increasing character. The captured associations from the case study are based on the question: what happens to the value of the target term if the value of the source term grows? Following this structure, it is possible to define the transitive relationships between variables that are associated through the object properties ‘increase‘ or ‘decrease‘. Table 7-20 presents these SWRL rules and their meaning.

Table 7-20: SWRL Modelling of transitive Relation between ‘increase’ and ‘decrease’

#	Meaning	FOL Rule
1	Assuming that a growing value of variable b would decrease the value of variable c and a growing value of variable a would increase the value of variable b, a growing value of variable a would transitively decrease the value of variable c.	increase(?a, ?b) ^ decrease(?b, ?c) → decrease(?a, ?c)
2	Assuming that a growing value of variable b would decrease the value of variable c and a growing value of variable a would decrease the value of variable b, a growing value of variable a would transitively decrease the value of variable c.	decrease(?a, ?b) ^ increase(?b, ?c) → decrease(?a, ?c)
3	Assuming that a growing value of variable b would increase the value of variable c and a growing value of variable a would increase the value of variable b, a growing value of variable a would transitively increase the value of variable c.	increase(?a, ?b) ^ increase(?b, ?c) → increase(?a, ?c)
4	Assuming that a growing value of variable b would decrease the value of variable c and a growing value of variable a would decrease the value of variable b, a growing value of variable a would transitively increase the value of variable c.	decrease(?a, ?b) ^ decrease(?b, ?c) → increase(?a, ?c)

This way of modelling allows contradictory relations between the same pairs of variables and the object properties are not set as disjoint. Thus, the PPES may also reveal conflicts in PS performance optimization that are not visible at first glance, also not by the interviewed experts. However, the study has to ensure that these conflicts are not based on inconsistencies in the ontology. This can be analysed as soon as the ontology is populated with individuals. This procedure is be discussed in Section 7.7.

7.7 PPES Verification

This section discusses the PPES verification to prove the validity of the expert system and its generated axioms. First, the current ontology is populated with individuals. These individuals are exemplary instances of the previously created concepts and are interconnected through object property relations. In the second step, based on the developed SWRL rules, the reasoner of Protégé is able to infer the direct and transitive impact associations between those individuals. As first part of the validation, the direct impact associations must fit to the records from the CLM in order to prove the overall correctness of the rules. In addition, the logics of transitivity are validated by testing selected axioms against historical data from the case study company.

7.7.1 Ontology Population and Reasoning

To prove the logical correctness and to generate new knowledge from the PPES, a technique called ontology reasoning is applied. Reasoning is based on the principle of logical inference and can be characterized by discovering new relationships. Automatic procedures are able to generate new relationships based on existing data and an additional set of rules. Protégé allows adding these new relationships to the existing ontology data, persistently, or to return them only at query time. The choice depends on the ontology application requirements (W3C, 2015). In addition, there is a difference between ontology-based reasoning and rule-based reasoning. Ontology-based reasoning is based on the specifications of concepts and object properties as discussed earlier in this chapter. The inference rules for RDF-S or OWL are standardized and fixed. Therefore, no explicit rules need to be created. This type of reasoning generates, for instance, relationships between concepts in terms of equivalency or parent classification. The rule-based reasoning is purely dependent on the definition of semantic rules and allows forward- and backward-chaining classification of individuals. Rule-based inference requires a language for representing the rules and a rule engine (Oleksiy, 2018). When following the rule-based approach, consideration needs to be given to the concept that new knowledge will only be created at an individual level and not at a concept level. Thus, even if an ontology responsible person decides to store the new axioms persistently as additional ontology data, it will not affect the definition of concepts or their object property relations. Since FOL and, therefore, SWRL also, are always focussed on particular instances of a concept, the ontology needs to be populated with a set of individuals. Although the SWRL rules could be executed without individual data, the inference engine will not find any new axiom.

The individuals are generated within a Microsoft Excel spreadsheet based on the given concepts and their relationships through object properties. It is necessary to split individuals from the same class if other individuals use them through the same object property but in a different context. For instance, there are several instances of the concept ‘Alpha’ since each of the 4M has a specific and independent value. Each alpha-individual is unique and refers to a different object in the real world, thus, the reasoner needs to differentiate in order to generate meaningful new axioms. All individuals use the standard prefix ‘x’ to differentiate them clearly from similarly named concepts, for instance, ‘xTool’, ‘xMotivation’ or ‘xPattern’. To differ between individuals which belong to the same class, identifiers are created through concatenation of source concept name and target concept name per object property relation. Following this procedure, the alpha-individuals are called ‘xAlpha_PS’, ‘xAlpha_WIP’, ‘xAlpha_Tool’, ‘xAlpha_Process’ and ‘xAlpha_Operator’. The names of individuals, which refer to complex SWRL rules, may consist of multiple parts. For instance, ‘xDegree_Exhausting_WearLimit_MachineComponent’ belongs to the class ‘Degree’. It is important to the model quality that all individuals follow this standard; otherwise, the inference engine will not work properly. Once the individuals are prepared in the spreadsheet, they are imported to Protégé. During the import, the individuals are mutually associated using the given object property relations from the parent concepts. Figure 7-23 shows the sample relations between individuals.

The figure shows that the individual ‘xEM’ is classified as ‘EM’ and has object property relations to individuals from the concepts ‘QualificationLevel’, ‘Costs’ and ‘Availability’. After the import, and according to the count of logical associations, the ontology consists of 272 individuals.

Figure 7-23: Imported Relations between Individuals in Protégé

Protégé uses ‘HermiT’ as the standard reasoning software that supports all features of the OWL 2 ontology language as well as SWRL rules. ‘HermiT’ was written in Java and consists of components for loading, classification, realisation, blocking, existential expansion and reasoning. The architecture style also allows an easy integration into other applications. During the loading process of an ontology, the OWL format is converted into a set of assertions and descriptive-logical clauses. Thus, internally, ‘HermiT’ represents an ontology as a set of first-order logical rules. The reasoning itself applies a forward-chaining and backward-chaining inference procedure, which allows a comprehensive analysis of transitive effects. Thus, it is not required to specify any order for the execution of SWRL rules during the reasoning (Glimm et al., 2014). The tool allows specific configurations that affect the inference results and can be found in Figure 7-24.

The configuration dialogue is separated into class inference, object property inference, data property inference and individual inference. Each section serves a specific reasoning goal. For instance, disjoint or equivalent classes can be implied from a particular OWL definition. The PPES is focussed on individual inferences and specifically on object property assertions between individuals. By deselecting the other settings that are not required, the reasoning performance improves. It is also possible to configure the initialization procedure by changing the priority of precomputations. However, since the initialization performs well, it is not necessary to change the default settings. Once the reasoning results are effective, it is possible to store them permanently to the ontology. Otherwise, they will disappear as soon as the reasoner is deactivated again.

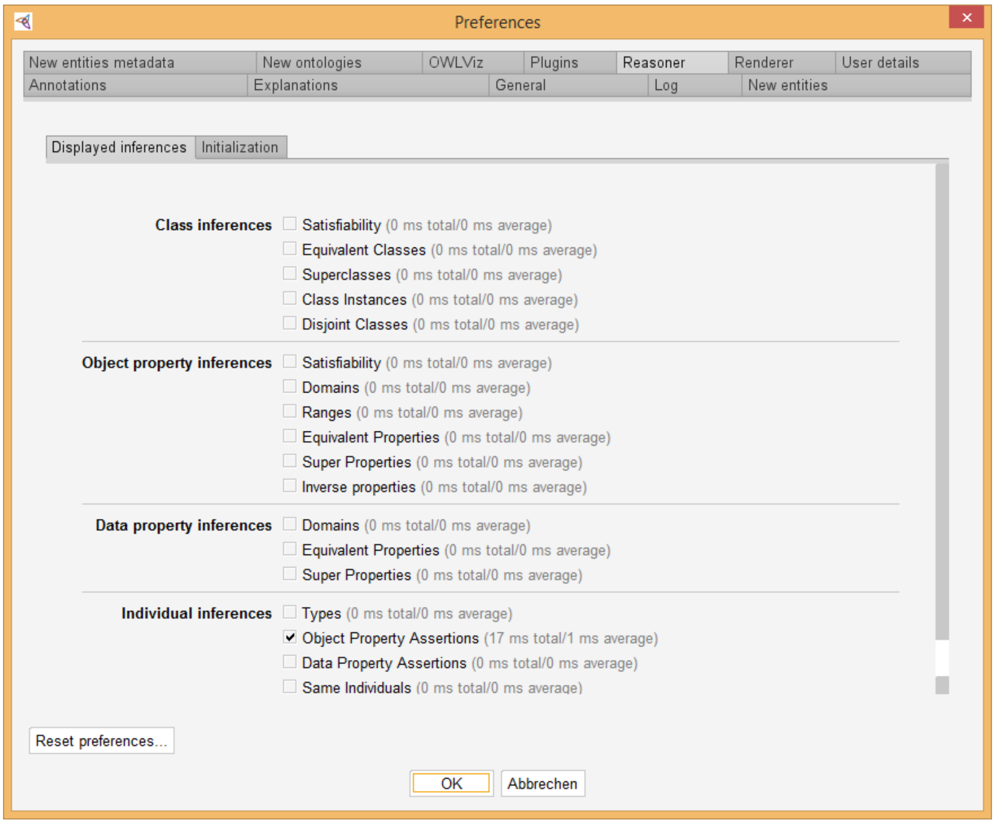


Figure 7-24: Configuration for the Protégé Reasoner for PPES

While the reasoner is active, the inferred object property assertions are highlighted and can be visually separated from the others that are explicitly defined. This is helpful during the analysis phase to distinguish between the term expressions and the inferred axioms. For practical usage of the PPES in a company, this separation is no longer important, thus, the inferred axioms can be persisted at the end of the study.

7.7.2 Proof of Correctness of Inferred Axioms

To prove the correctness of the SWRL rules and the populated ontology, the PPES has been separated into two single OWL files. One file consists only of SWRL rules that cover logical associations obtained from the case study and the other file includes the transitivity rules from Table 7-20 in addition. When running the inference engine, the file without transitivity rules needs to generate exactly those inferences, which are stated through the SWRL rules.

The absolute number of inferred axioms is 350, and therefore, differs from the number of SWRL rules, which is 272. However, the reason for this difference is the way of modelling the ontology with individuals, which can have different types as shown in Figure 7-25. The causal relationship diagram differs between offline PdM, online PdM and unspecified PdM. Though the SWRL rules and the class model differentiate between these, the related individuals ‘xOffline’ and ‘xOnline’ are also subclasses of ‘PdM’. Thus, the inference engine implies that the stated associations for unspecified PdM are also valid for online PdM and offline PdM. From the initial 40 explicit associations, the inference engine generated 88 axioms. This kind of transitivity was not explicitly specified within SWRL but is in OWL standard, and works correctly.

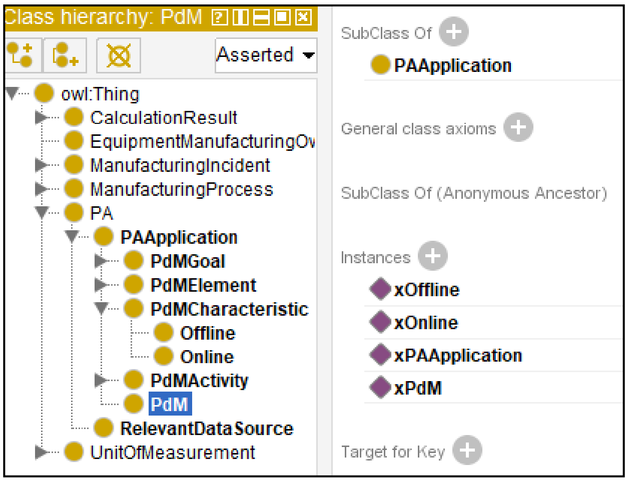


Figure 7-25: Differentiation between Offline, Online and Unspecified PdM

Implicit transitivity can also be found for individuals from classes that are specified as equivalent, for instance ‘xProcess’ and ‘xSingleProcess’. Thus, the inference engine generates 8 axioms from 4 explicit associations since both individuals are treated as equivalent. These and similar cases lead to a higher number of axioms compared to the explicitly stated associations. After the verification of each implication, the logical correctness of the PPES is proved.

For the second file, which contains the explicit transitivity rules in addition, the inference engine generates 1045 object property assertions for individuals. To obtain the number of only transitive axioms, the 350 axioms from the first file need to be subtracted. This calculation leads to 695 implied logical associations between 60 source and 41 target individuals. This means that the interviewed experts did not identify these effects and that they were potentially not aware of their existence before. Concerning the count of individuals which take part in all associations, it is possible to rate the most influencing and influenced ones including these transitive effects. The analysis reveals that 18% of all source individuals are the influencing factors within 50% of all object property assertions. Table 7-21 lists the most influencing source terms.

Table 7-21: Most Influential Individuals rated by Occurrence in Associations

Source	Occurrences in associations	Percentage of occurrences	Accumulation
xOnline	62	6,03%	6,03%
xOffline	60	5,83%	11,86%
xPercentage_ReactiveMaintenance	59	5,73%	17,59%
xPAApplication	53	5,15%	22,74%
xPdM	53	5,15%	27,89%
xMaturity_Process	32	3,11%	31,00%
xPercentage_PreventiveMaintenance	31	3,01%	34,01%
xStability_Process	30	2,92%	36,93%
xEfficiency_Coordination_EMProcess	27	2,62%	39,55%
xDegree_ToolDedication	26	2,53%	42,08%
xNumber_Failure	26	2,53%	44,61%
xDegree_Exhausting_WearLimit_ MachineComponent	24	2,33%	46,94%
xDuration_Downtime_Equipment	24	2,33%	49,27%
xEfficiency_SparePartLogistics	24	2,33%	51,60%

Another aspect of the analysis is to identify the most influenced individuals. The analysis shows that 11% of all target individuals are influenced within 50% of all object property assertions. Table 7-22 lists the most influenced target terms.

Table 7-22: Most Influenced Individuals rated by Occurrence in Associations

Target	Occurrences in associations	Percentage of occurrences	Accumulation
xLittle'sLaw	81	7,87%	7,87%
xAlpha_PS	74	7,19%	15,06%
xUtilization_Equipment	73	7,09%	22,16%
xFF	57	5,54%	27,70%
xCT	47	4,57%	32,26%
xDuration_StandbyTime	39	3,79%	36,05%
xDGR	39	3,79%	39,84%
xWIP	37	3,60%	43,44%
xInventory	37	3,60%	47,04%
xWSPW	37	3,60%	50,63%

Overall, 135 individuals participate in effect associations either as target, source or both. In fact, they refer to the 134 terms that were obtained during the case study. Since ‘xInventory’ is not explicitly documented as a single term but specified as equivalent to ‘xWIP’, the actual number of individuals from distinct classes is equal to the number of terms. This result is a further indicator that the PPES is correctly representing the raw associations from the CLM.

7.7.3 Empirical Validity

After verifying the general correctness of the PPES, the transitively generated axioms can be validated against historical data. These types of data are gathered from the BI system that is applied at the case study company. The validation procedure works as follows:

- Select a transitively generated effect association from the PPES that consists of two classified individuals.
- Extract historical data from the last 6 months that quantify both individuals.
- Analyse the historical trends of both variables by calculating the correlation coefficient *r*.
- Evaluate *r* in order to state if the type of correlation fits to the result generated by PPES.

The result for *r* indicates the strength and direction of an association between the selected variables. Generally, *r* can have a value ranging between –1.0 and +1.0, where 0 means that there is no association between the selected variables. A negative value of *r* indicates that increasing values of variable *a* correlate to decreasing values of variable *b*. A positive value of *r* means that increasing values of variable *a* correlate also to increasing values of variable *b*. A conventional approach to interpret *r* considers values from 0 to 0.09 (or 0 to –0.09) as negligible relationships, whereas 0.9 to 1.0 (or –0.9 to –1.0) indicate a very strong relationship. Further categories are weak correlation (0.10 to 0.39 or –0.10 to –0.39), moderate correlation (0.40 to 0.69 or –0.40 to –0.69) and strong correlation (0.70 to 0.89 or –0.70 to –0.89) (Schober et al., 2018). Though a correlation does not state the actual causal relation, it can be applied to verify the logical correctness of the axioms generated by PPES. The validation tests mainly against linear correlation between two variables; only if no linear relationship can be detected, the association is additionally tested using the Spearman's Rank-Order Correlation (Laerd, n.d.).

The validation procedure is applied to six selected transitive effect associations. It is expected that by validating the transitive axioms, the underlying axioms stated by experts are implicitly valid as well. Because the BI system does only contain measures for a subset of the PPES concepts, the selection of associations depends on the existence of historical data – otherwise, the validation would not be effective. Following associations have been selected to verify the empirical validity of the PPES:

1) Impact of Percentage of Rework on Utilization
2) Impact of Going Rate on Wafer Starts Per Week
3) Impact of Work in Progress on Flow Factor
4) Impact of Machine Downtime on Work in Progress
5) Impact of Machine Uptime on Overall Equipment Efficiency
6) Impact of Percentage of Rework on Going Rate

The analysis and evaluation of each association is discussed in the following sub-sub-sections. To gain consistent test results, the historical data belongs to the same product and operations data for all test cases. The selected operations area is the evaporation workshop, whereas the selected product is one of the high-volume frontend product types that is manufactured at the case study facility. Since the PPES creates only qualitative axioms, even a weak correlation is seen as empirically valid if it points in the direction that was stated by PPES.

7.7.3.1 Impact of Percentage of Rework on Utilization

Based on the inference engine, the utilization of production machines decreases if the percentage of rework would increase. Figure 7-26 shows the visualized trends of the historical data for both variables. The value bars are hidden since the data refers to sensitive performance information. This statement refers also to the following trend charts.

The analysis shows that $r = -0.28$. This value indicates a weak correlation where increasing values of rework percentage are associated to decreasing values of utilization. This result verifies the correctness of the underlying axiom that was generated by PPES.

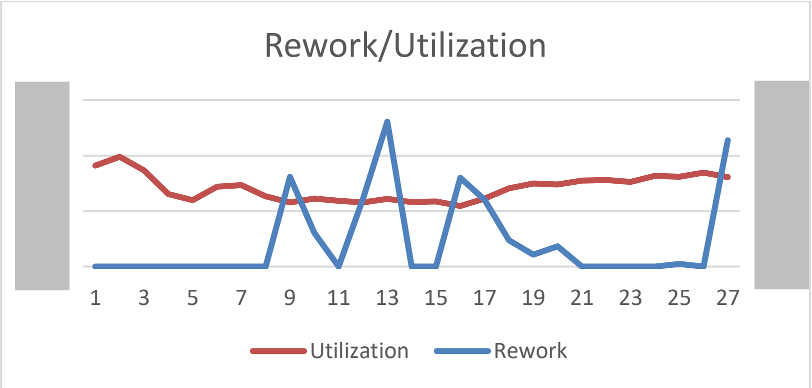


Figure 7-26: Trend chart for Rework and Utilization

7.7.3.2 Impact of Going Rate on Wafer Starts Per Week

A further axiom states that an increasing GR leads to increasing WSPW. The test data for WSPW is not limited to single operation areas but logistically related to the entire FOL area. Figure 7-27 shows the visualized trends of the historical data for both variables.

The analysis shows that $r = 0.54$. This value indicates a moderate correlation where increasing values of GR are associated to increasing values of WSPW. This result verifies the correctness of the underlying axiom that was generated by PPES.

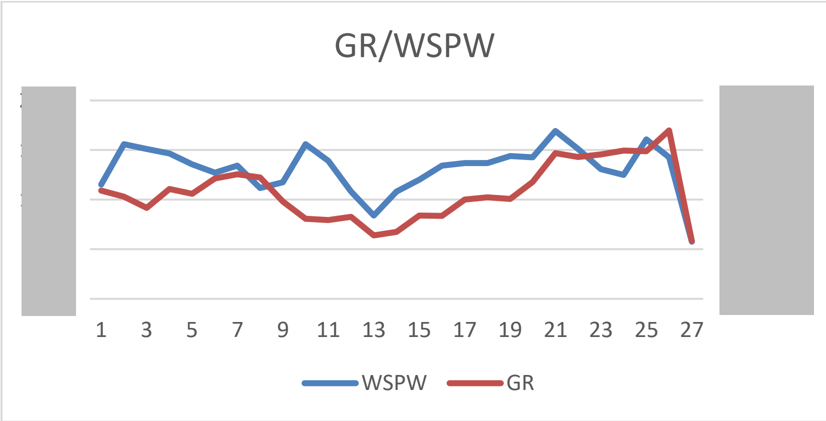


Figure 7-27: Trend chart for GR and WSPW

7.7.3.3 Impact of Work in Progress on Flow Factor

The PPES generated an axiom saying that an increasing level of WIP leads to increasing values of FF. Figure 7-28 shows the visualized trends of the historical data for both variables.

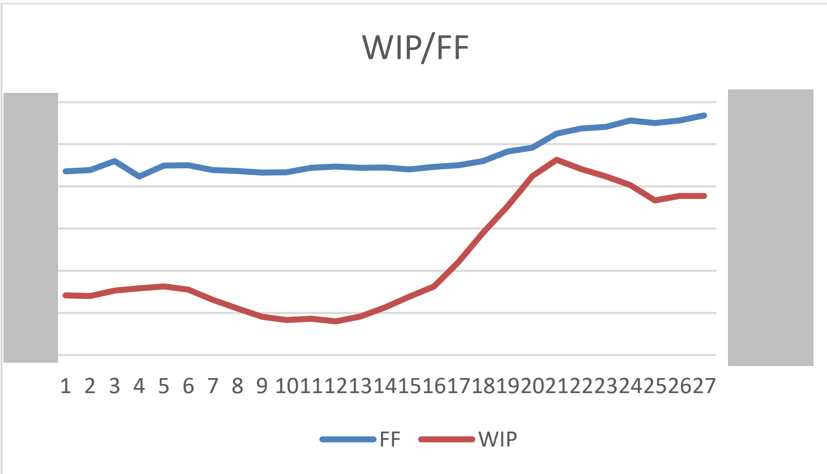


Figure 7-28: Trend chart for WIP and FF

The analysis shows that *r* = 0.89. This value indicates a strong and nearly very strong correlation where increasing values of WIP are associated to increasing values of FF. This result verifies the correctness of the underlying axiom that was generated by PPES.

7.7.3.4 Impact of Machine Downtime on Work in Progress

Another axiom states that increasing machine downtimes cause increasing WIP. Figure 7-29 shows the visualized trends of the historical data for both variables.

The analysis could not detect a linear relationship. Therefore, the data is tested against non-linear associations. This additional analysis results in *r* = 0.26, which indicates a weak correlation where increasing machine downtimes are associated to increasing values of WIP. This result verifies the correctness of the underlying axiom that was generated by PPES.

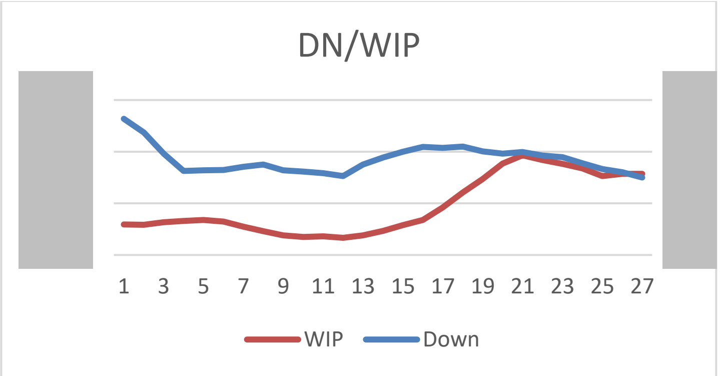


Figure 7-29: Trend chart for Downtime and WIP

7.7.3.5 Impact of Machine Uptime on Overall Equipment Efficiency

The PPES suggests that an increasing machine uptime causes an increasing OEE. Figure 7-30 shows the visualized trends of the historical data for both variables.

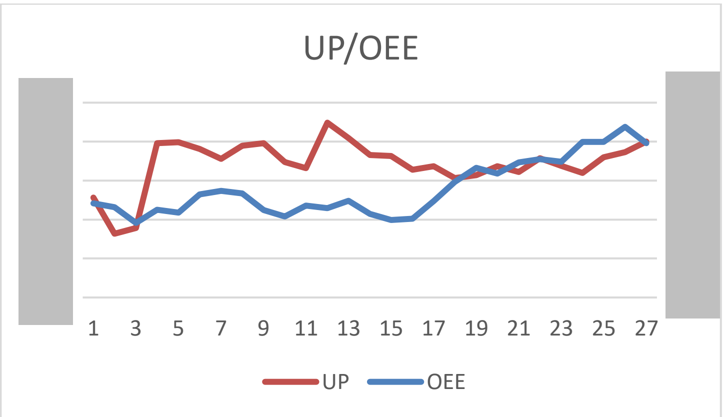


Figure 7-30: Trend chart for Uptime and OEE

The analysis shows that $r = 0.23$. This value indicates a weak correlation where increasing values of uptime are associated to increasing values of OEE. This result verifies the correctness of the underlying axiom that was generated by PPES.

7.7.3.6 Impact of Percentage of Rework on Going Rate

The final selected axiom indicates that an increasing percentage of rework leads to a decreasing going rate. Figure 7-31 shows the visualized trends of the historical data for both variables.

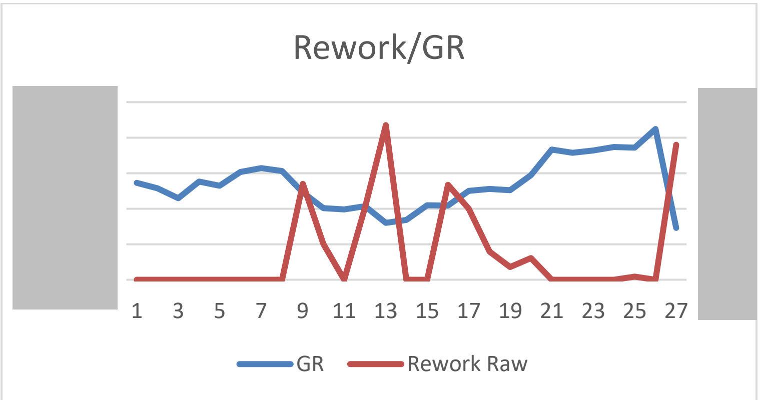


Figure 7-31: Trend chart for Rework and GR

The analysis shows that $r = -0.58$. This value indicates a moderate correlation where an increasing percentage of rework is associated to increasing values of GR. This result verifies the correctness of the underlying axiom that was generated by PPES.

After executing and passing all test cases, the verification of the empirical validity of PPES is fulfilled.

7.8 PPES Analysis and Evaluation

This section discusses the PPES analysis and evaluation and presents new knowledge about the impacts of PdM on PS elements generated through transitive logical inference, which experts did not mention. To analyse the new transitive knowledge, it is necessary to distinguish between inferred axioms from the explicit effect associations and the transitive dependencies. For this purpose, the already separated PPES OWL files need to be queried independently. Each ontology executes the reasoner and stores the inferred axioms to the ontology files persistently. To extract the individuals and their effect associations, the project applies the Simple Protocol and Rdf Query Language (SPARQL). The Structured Query Language (SQL), which is a standard for managing data in relational database management systems, inspires SPARQL. Both ontologies are queried using following script:

```
SELECT DISTINCT ?source  ?decrease ?increase
WHERE {
{?source  prop:decrease ?b;
prop:decrease ?decrease }
UNION  {?source  prop:increase ?b ;
            prop:increase ?increase}
}
ORDER BY ?source
```

After executing the SPARQL script, Protégé returns the information in a table format for the file without transitivity rules as shown in Figure 7-32 .

source	decrease	increase
xAvailability_EM	xDuration_StandbyTime	
xAvailability_EM	xDuration_UnscheduledDown	
xAvailability_EM		xAvailability_Equipment
xAvailability_Equipment	xFF	
xAvailability_Equipment	xVariance_WIP	
xAvailability_Equipment	xAlpha_Tool	
xAvailability_Equipment		xDGR
xAvailability_Equipment		xAvailability_PS
xAvailability_Equipment		xCapacity_Equipment
xAvailability_Equipment		xGR
xAvailability_Equipment		xOEE
xAvailability_Operator	xVariance_WIP	
xAvailability_Operator	xCT	
xAvailability_Operator	xDuration_StandbyTime	
xAvailability_Operator	xFF	
xAvailability_Operator		xAvailability_PS
xAvailability_Operator		xGR
xAvailability_Operator		xDGR
xAvailability_Process		xDGR
xAvailability_Process		xCapacity_Equipment

Figure 7-32: Sample Result for inferred Effect Associations using SPARQL

The records from both query results are copied into an Excel spreadsheet for detailed comparison. A created formula searches for matching records within both lists and returns an 'x' if it does not find any matching. An 'x' states that the record is a transitively inferred axiom. Figure 7-33 shows an excerpt from the comparison results where the column 'Transitive' marks the relevant records.

Source	Type	Target	Transitive
xAlpha_Tool	increase	xAlpha_PS	x
xAvailability_EM	decrease	xUtilization_Equipment	
xAvailability_EM	decrease	xVariance_CT	x
xAvailability_EM	decrease	xVariance_WIP	x
xAvailability_EM	decrease	xAlpha_PS	x
xAvailability_EM	decrease	xDuration_StandbyTime	
xAvailability_EM	decrease	xWIP	x
xAvailability_EM	decrease	xCT	x
xAvailability_EM	decrease	xDuration_UnscheduledDown	
xAvailability_EM	decrease	xFF	x
xAvailability_EM	decrease	xInventory	x
xAvailability_EM	decrease	xAlpha_Tool	x
xAvailability_EM	decrease	xLittle'sLaw	x

Figure 7-33: Record Comparison to reveal only Transitive Associations

To limit the analysis to PdM only, the records are filtered by the source individuals 'xPdM', 'xOffline' and 'xOnline'. As mentioned in the previous chapter, 'xOffline' and 'xOnline' contain all logical associations of 'xPdM', thus, the redundant associations need to be removed.

The analysis classifies the records based on the impact of PdM on the SI PS as positive or negative. As expected in Section 7.6, PPES generated contradictory results. Because the model has been verified as logically correct, this kind of conflict is not based on an inconsistency in data or rules, but rather indicates that the application of PdM might lead to positive as well as negative effects on a certain PS element (depending on the involved nodes in the transitive network).This finding confirms one part of hypothesis 1 that was stated in 2.6.2. Table 7-24 shows the inferred axioms with conflicts where a qualified effect is not possible to state clearly. These records show transitively generated associations where PdM as source individual points to the same target individual but with an opposite effect.

Table 7-23: Transitive Impacts of PdM on SI PS with Conflicts

#	Source	Type	Target
1	xPdM	decrease + increase	xAlpha_PS
2	xPdM	decrease + increase	xUtilization_Equipment
3	xOffline	decrease + increase	xSpeed_Reaction
4	xPdM	decrease + increase	xLittle'sLaw

To understand the reasons for these contradictions, the records are analysed in more detail. Record #1 states that PdM would have a contradictory impact on the PS variability (Alpha PS). Figure 7-34 shows the explanation from the inference engine for the decreasing effect. Unfortunately, the order of the statements in the explanation does not cover the exact logical dependencies. Hence, the prose explanation may neither start with the first line nor continues in the order of the Protégé reasoner explanation. This consideration is valid for all following explanations as well.

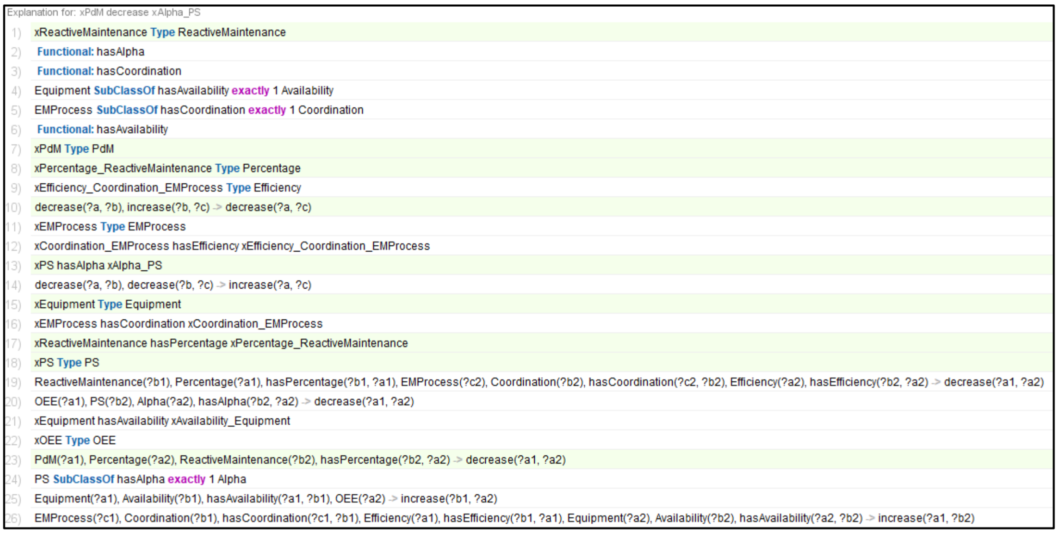


Figure 7-34: Explanation for inferred Axiom: xPdM decrease xAlpha_PS

The explanation shows that the application of PdM deceases the percentage of reactive maintenance (line 23). Actually, an increasing percentage of reactive maintenance would decrease the efficiency of coordination of EM processes. Due to the transitivity rule in line 14, this effect is reversed. As the efficiency increases, the equipment availability increases as well (line 26), which causes an increasing OEE (line 25). By improving the OEE, the PS variability decreases (line 20). This is why PdM would transitively decrease Alpha PS, which is a positive effect.

There are also explanations for the axiom that PdM would increase Alpha PS, which is a negative effect. Figure 7-35 shows one selected explanation. It says that the frequency of scheduled downtimes would increase by application of PdM (line 2). An increased frequency would lead to an increased PS variability (line 10). Due to the transitivity rule in line 5, PdM would have an increasing influence on Alpha PS. Though the underlying axiom in line 10 was stated by experts, it must be highlighted that PPES also suggests that PdM would decrease the frequency of unscheduled downtimes and that the reduction of downtimes would also decrease the Alpha PS. This finding indicates that a production manager must find the right balance between a higher frequency of scheduled downtimes and the overall equipment downtime in order to gain benefits from PdM.

```
Explanation for: xPdM increase xAlpha_PS
1)  xPS Type PS
2)  PAApplication(?a1), PdM(?a1), ScheduledDown(?a2), hasFrequency(?a2, ?b2), Frequency(?b2) -> increase(?a1, ?b2)
3)  xAlpha_PS Type Alpha
4)  xPdM Type PdM
5)  increase(?a, ?b), increase(?b, ?c) -> increase(?a, ?c)
6)  ScheduledDown SubClassOf hasFrequency exactly 1 Frequency
7)  Functional: hasFrequency
8)  xScheduledDown Type ScheduledDown
9)  xPS hasAlpha xAlpha_PS
10) ScheduledDown(?a1), Frequency(?b1), hasFrequency(?a1, ?b1), PS(?b2), Alpha(?a2), hasAlpha(?b2, ?a2) -> increase(?b1, ?a2)
11) xScheduledDown hasFrequency xFrequency_ScheduledDown
12) PdM SubClassOf PAApplication
```

Figure 7-35: Explanation for inferred Axiom: xPdM increase xAlpha_PS

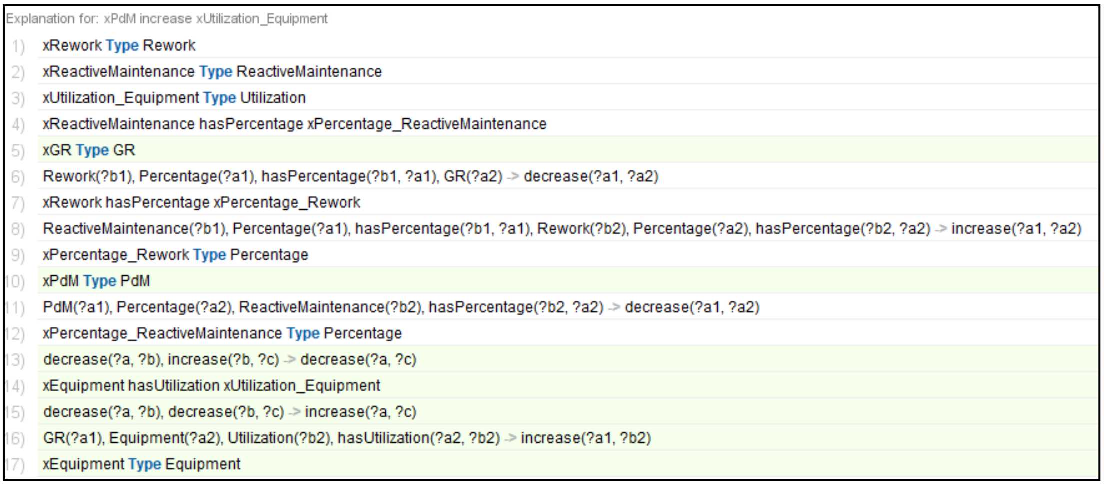
Record #2 mentions that PdM could decrease and increase equipment utilization. To understand from where the conflicting effects come, the inference engine provides several explanations. Figure 7-36 shows one explanation for the statement that: PdM decreases the equipment utilization.

```
Explanation for: xPdM decrease xUtilization_Equipment
1)  ReactiveMaintenance(?b1), Percentage(?a1), hasPercentage(?b1, ?a1), Equipment(?a2), Downtime(?b2), hasDowntime(?a2, ?b2), Duration(?c2), hasDuration(?b2, ?c2) -> increase(?a1, ?c2)
2)  Equipment(?a1), Downtime(?b1), hasDowntime(?a1, ?b1), Duration(?c1), hasDuration(?b1, ?c1), Equipment(?a2), Availability(?b2), hasAvailability(?a2, ?b2) -> decrease(?c1, ?b2)
3)  xReactiveMaintenance Type ReactiveMaintenance
4)  xUtilization_Equipment Type Utilization
5)  xReactiveMaintenance hasPercentage xPercentage_ReactiveMaintenance
6)  Functional: hasDowntime
7)  Equipment(?a1), Capacity(?b1), hasCapacity(?a1, ?b1), Equipment(?a2), Utilization(?b2), hasUtilization(?a2, ?b2) -> decrease(?b1, ?b2)
8)  xEquipment hasAvailability xAvailability_Equipment
9)  xEquipment hasCapacity xCapacity_Equipment
10) xAvailability_Equipment Type Availability
11) Equipment SubClassOf hasDowntime min 1 Downtime
12) xDowntime_Equipment hasDuration xDuration_Downtime_Equipment
13) xDuration_Downtime_Equipment Type Duration
14) xPdM Type PdM
15) xPercentage_ReactiveMaintenance Type Percentage
16) PdM(?a1), Percentage(?a2), ReactiveMaintenance(?b2), hasPercentage(?b2, ?a2) -> decrease(?a1, ?a2)
17) decrease(?a, ?b), increase(?b, ?c) -> decrease(?a, ?c)
18) xEquipment hasUtilization xUtilization_Equipment
19) xCapacity_Equipment Type Capacity
20) Equipment(?a1), Availability(?b1), hasAvailability(?a1, ?b1), Equipment(?a2), Capacity(?b2), hasCapacity(?a2, ?b2) -> increase(?b1, ?b2)
21) decrease(?a, ?b), decrease(?b, ?c) -> increase(?a, ?c)
22) xEquipment hasDowntime xDowntime_Equipment
23) xEquipment Type Equipment
```

Figure 7-36: Explanation for inferred Axiom: xPdM decrease xUtilization_Equipment

The explanation indicates that an application of PdM would directly decrease the percentage of reactive maintenance (line 14). This percentage would normally increase the downtime duration (line 1), whereby the equipment availability would be decreased (line 2). If the equipment availability increased, the equipment capacity would also increase (line 20). An increasing equipment capacity decreases the utilization of this equipment (line 6). The reason for generating this axiom is that PPES does not consider that production planning experts could increase the weekly wafer starts to enhance the production volume in order to utilize the advanced equipment capacity. Indeed, other transitive effects created by PPES suggest that PdM would lead to increased WSPW. Though this effect is expected to increase the production volume, it was not explicitly stated by the IE experts and is therefore missing in the SWRL rules. Hence, it cannot be considered when the equipment capacity is increased. Assuming that experts retrieve this type of impact of PdM from PPES, a reduced equipment utilization caused by PdM could be avoided. Nevertheless, as it was discussed in Sub-Section 2.5.2, PdM can only be applied to a limited number of machines within an economically useful timeframe. Therefore, the production volume cannot be simply increased without considering the capacity situations at other workcenters that are not managed via PdM. Otherwise, the percentage of bottleneck machines could increase, which has negative effects on the material flow: PPES implied negative effects such as decreased number of weekly wafers starts, increased flow factor and increased variability (alpha) of the entire production system. In addition, if those machines that serve upstream operations on a production route become bottlenecks, the utilization of the PdM-managed machine may not be affected at all. Due to this complexity, the effect cannot be simply eliminated without further research that involves production planning experts. Hence, the concept ‘ProductionPlanning’ was added to the ontology tree as a new grouping concept consisting of the already existing concept ‘PlanningProcedure’. This new concept can be used as interface to add further knowledge from the production planning domain in future research projects. Nevertheless, for this PhD project it was argued that the inferred axiom is logically correct: if the equipment capacity increases at a constant production volume, the equipment utilization decreases accordingly.

There are also several explanations for the statement that an application of PdM would increase the equipment utilization. Figure 7-37 shows an example for this kind of transitivity.


Explanation for: xPdM increase xUtilization_Equipment

1) xRework Type Rework
2) xReactiveMaintenance Type ReactiveMaintenance
3) xUtilization_Equipment Type Utilization
4) xReactiveMaintenance hasPercentage xPercentage_ReactiveMaintenance
5) xGR Type GR
6) Rework(?b1), Percentage(?a1), hasPercentage(?b1, ?a1), GR(?a2) -> decrease(?a1, ?a2)
7) xRework hasPercentage xPercentage_Rework
8) ReactiveMaintenance(?b1), Percentage(?a1), hasPercentage(?b1, ?a1), Rework(?b2), Percentage(?a2), hasPercentage(?b2, ?a2) -> increase(?a1, ?a2)
9) xPercentage_Rework Type Percentage
10) xPdM Type PdM
11) PdM(?a1), Percentage(?a2), ReactiveMaintenance(?b2), hasPercentage(?b2, ?a2) -> decrease(?a1, ?a2)
12) xPercentage_ReactiveMaintenance Type Percentage
13) decrease(?a, ?b), increase(?b, ?c) -> decrease(?a, ?c)
14) xEquipment hasUtilization xUtilization_Equipment
15) decrease(?a, ?b), decrease(?b, ?c) -> increase(?a, ?c)
16) GR(?a1), Equipment(?a2), Utilization(?b2), hasUtilization(?a2, ?b2) -> increase(?a1, ?b2)
17) xEquipment Type Equipment

Figure 7-37: Explanation for inferred Axiom: xPdM increase xUtilization_Equipment

The explanation again shows that the application of PdM reduces the percentage of reactive maintenance (line 11). Usually, a higher percentage of reactive maintenance would increase the percentage of rework (line 8). However, due to the transitivity rule in line 13, PdM decreases transitively the percentage of rework. Based on the transitivity rule in line 15, a decreased percentage of rework increases the GR (which is the opposite of the rule in line 6). An increased GR leads to an increased equipment utilization (line 16), and this is why the application of PdM transitively increases the equipment utilization.

Record #3 indicates contradictory effects regarding speed of reactions when applying ‘offline’ PdM in particular. Basically, an increased speed would mean a positive effect. The peculiarity of this record is that the transitive axiom contradicts an expert statement. Figure 7-38 shows the explanation for offline PdM decreases the speed of reaction. It only refers to the underlying SWRL rule that is stated in line 6 and which is based on the expert responses.

Explanation for: xOffline decrease xSpeed_Reaction

1) xReaction hasSpeed xSpeed_Reaction
2) xReaction **Type** Reaction
3) xOffline **Type** PdM
4) xSpeed_Reaction **Type** Speed
5) xOffline **Type** PAApplication
6) Reaction(?b2), PAApplication(?a1), PdM(?a1), hasSpeed(?b2, ?a2), Speed(?a2), Offline(?a1) -> decrease(?a1, ?a2)
7) xOffline **Type** Offline

Figure 7-38: Explanation for inferred Axiom: xPdM decrease xSpeed_Reaction

Figure 7-39 shows one selected explanation for the axiom that offline PdM would increase the speed of reaction.

Explanation for: xOffline increase xSpeed_Reaction

1) xReaction hasSpeed xSpeed_Reaction
2) xPercentage_PreventiveMaintenance **Type** Percentage
3) xReaction **Type** Reaction
4) xOffline **Type** PdM
5) increase(?a, ?b), increase(?b, ?c) -> increase(?a, ?c)
6) xPreventiveMaintenance hasPercentage xPercentage_PreventiveMaintenance
7) xPreventiveMaintenance **Type** PreventiveMaintenance
8) xSpeed_Reaction **Type** Speed
9) PreventiveMaintenance(?b1), Percentage(?a1), hasPercentage(?b1, ?a1), Reaction(?b2), Speed(?a2), hasSpeed(?b2, ?a2) -> increase(?a1, ?a2)
10) PdM(?a1), Percentage(?a2), hasPercentage(?b2, ?a2), PreventiveMaintenance(?b2) -> increase(?a1, ?a2)

Figure 7-39: Explanation for inferred Axiom: xPdM increase xSpeed_Reaction

It states that PdM would increase the percentage of preventive maintenance (line 10). An increased percentage would also increase the speed of reactions (line 9). Due to the transitivity rule in line 5, PdM increases the speed of reaction. Since the individual 'xOffline' was classified as sub-type of the concept 'PdM' in the ontology (line 4), the reasoner implies that this axiom is also valid for offline PdM. Probably, the contradiction is based on the fact that experts compared the direct benefits and drawbacks of offline versus online PdM; in this direct comparison, the experts had the impression that the EM staff might react slower if they would only rely on offline PdM solutions without consideration of the current machine performance. However, as offline PdM helps to detect new failure patterns (see 6.3.1), these insights can be used to avoid these types of failures by preventive actions. Hence, the core statement that offline PdM leads to slower reaction is only true in the context of comparing the capabilities of different PdM applications, but not in general.

Record #4 is generally not seen as reasonable though the underlying axioms were stated by experts. A tool or strategy like PdM is not expected to influence a general 'law'. Since Little's Law defines the relation between GR, WIP and CT (see Equation 4.6 in 4.4.1), the effects implied from PPES cannot be qualified even without contradiction: it is not useful to 'increase' or 'decrease' a law. However, PPES suggests that PdM has straight positive impacts on the components of this formula.

In reality, all of these conflicting effects are most probably not of the same value, thus, they will not cancel each other out. A simulation model can perform quantified analyses to differentiate the value of the effects. This method is described in Chapter 8.

Table 7-24 lists the transitively inferred axioms for PdM without any conflict including their qualified effect on SI PS performance and the associated area of challenge.The table shows that all of the non-conflicting transitive associations have a positive effect on the PS performance in SI. Based on the logics of PPES, this means that an application of PdM would not lead to any hidden negative effect on SI PS performance. In addition, the results prove that PdM is able to support SI companies in mastering challenges in SI value chains. Figure 7-40 consolidates in which way the abovementioned transitive improvements influence the ability to overcome particular challenges.

The aggregated results reveal that PdM is capable of supporting all categories of selected challenges plus 'Costs', which is beyond the thesis scope but seen as noteworthy based on the PPES assessment. As expected, PdM has the most significant influence on maintenance-oriented challenges. However, the performance in the areas of logistics, engineering and quality is likely to improve as well, which indicates a more effective handling of related challenges.

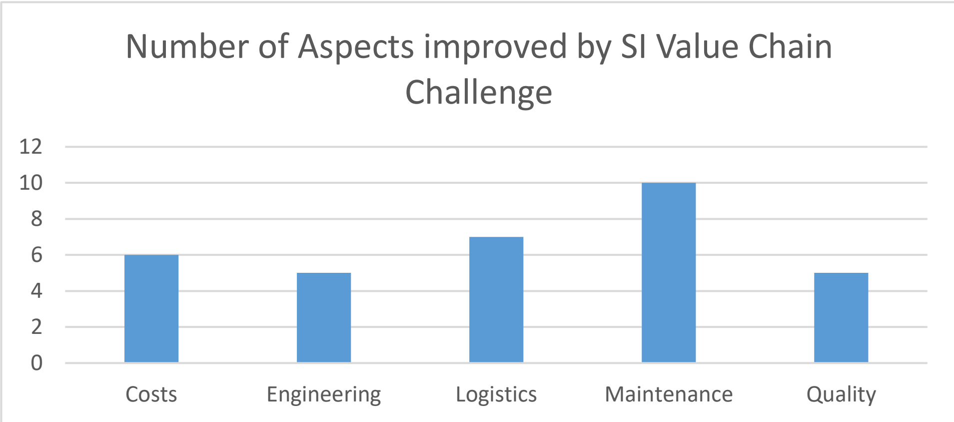


Figure 7-40: Number of Aspects improved by SI Value Chain Challenge

Table 7-24: Qualified transitive Impacts of PdM on SI PS without Conflicts

#	Source	Type	Target	Qualified Effect	Area of Challenge
1	xPdM	increase	xWSPW	Positive	Logistics
2	xPdM	increase	xQE	Positive	Quality
3	xPdM	increase	xYield	Positive	Quality
4	xPdM	increase	xDGR	Positive	Logistics
5	xPdM	increase	xMTBF	Positive	Maintenance
6	xPdM	increase	xAvailability_PS	Positive	Logistics
7	xPdM	increase	xAvailability_Equipment	Positive	Engineering
8	xPdM	increase	xOEE	Positive	Engineering
9	xPdM	increase	xCapacity_Equipment	Positive	Logistics
10	xPdM	increase	xQuality_Monitoring	Positive	Maintenance
11	xPdM	increase	xProbability_Prevention_TotalFailure	Positive	Maintenance
12	xPdM	increase	xQuality_PlanningProcedure	Positive	Maintenance
13	xPdM	increase	xSpeed_Analysis	Positive	Maintenance
14	xPdM	increase	xProbability_Prevention_CollateralDamage	Positive	Maintenance
15	xPdM	increase	xLifespan_Equipment	Positive	Engineering
16	xPdM	increase	xSpeed_Reaction	Positive	Maintenance
17	xPdM	increase	xDegree_Distribution_Evenness_Downtime	Positive	Engineering
18	xPdM	increase	xProbability_Prevention_LateEffect	Positive	Maintenance
19	xPdM	decrease	xCosts_Personnel	Positive	Costs

#	Sour ce	Type	Target	Qualified Effect	Area of Challenge
20	xPdM	decrease	xCosts_Product	Positive	Costs
21	xPdM	decrease	xVariance_CT	Positive	Logistics
22	xPdM	decrease	xPercentage_Rework	Positive	Quality
23	xPdM	decrease	xCosts_Inventory	Positive	Costs
24	xPdM	decrease	xDuration_StandbyTime	Positive	Engineering
25	xPdM	decrease	xScrap	Positive	Quality
26	xPdM	decrease	xCosts_EM	Positive	Costs
27	xPdM	Decrease	xWafersToScrap	Positive	Quality
28	xPdM	decrease	xMTTR	Positive	Maintenance
29	xPdM	decrease	xCosts_SparePart	Positive	Costs
30	xPdM	decrease	xVariance_WIP	Positive	Logistics
31	xPdM	decrease	xFF	Positive	Logistics
32	xPdM	decrease	xAlpha_WIP	Positive	Logistics
33	xPdM	decrease	xPercentage_NewInvest	Positive	Costs
34	xPdM	decrease	xNumber_OnShift	Positive	Maintenance

7.9 Summary

The creation process of the PPES has shown the importance of being precise in defining core terms and their mutual relationships. A human reader is able to set the meaning of more complex terms such as ‘Degree Of Evenness Of Distribution Of Equipment Downtimes’ in relation to the term ‘Equipment’. An inference engine, however, requires specific and precise information about the inner logics of such a term. Thus, the generation of distinct concepts, such as ‘Equipment’, ‘Degree’ and ‘Evenness’ was the necessary first step in this research. Several methods have been discussed to group concepts based on mathematical distance and human evaluation. This step was required to model the similarity between concepts of an ontology. Object properties serve two major goals: to model complex terms as logically associated concepts and to model the influences between concepts as collected during the case study. Several techniques have been discussed to configure the object property meanings correctly as the basis for the logical inference. Concepts, ontology tree and object property associations between concepts build the framework of the PPES. This framework defines the participants of the model and their fundamental relations.

To design the effects between concepts, the FOL-oriented SWRL was applied to the ontology. Each direct effect was modelled as SWRL rule. In addition, four rules were created to describe the specific logics of transitivity for PPES. These rules are essential to gain results for transitive effects between instances of particular concepts. To analyse and evaluate the PPES, a set of individuals was created where each individual refers to one or many concepts. The inference engine generated transitive effects from the SWLR rules only on an individual level, not on a concept level. Since individuals can have multiple concepts as types, the identified transitive effects could not be mapped directly to single concepts in each case. The effects are only valid for individuals that share the exactly same parent concepts. The PPES calculated 38 transitive effects, where four are conflicting. These effects represent new knowledge beyond the expert interview results and confirm hypothesis 1 from the conceptual framework. With its capabilities as ontology and its properly modelled content, the generated PPES solves RO 3.

Chapter 8 A Simulation Model for Evaluating Impacts of PdM on SI PS Performance

8.1 Introduction

The knowledge-based PPES provides important insights to understand the logical influences of PdM applications on SI PS performance in general. However, PPES cannot distinguish between single workcenters and to what degree they can be used to improve the PS performance. Furthermore, the new transitive knowledge reveals that there might be scenarios where the effects of PdM are negative, for instance, where equipment utilization is reduced.

To investigate the strengths and limitations of PdM, and in addition, to identify the preferable workcenter where an application of PdM would mostly improve the PS performance, a quantitative analysis is required. This chapter will propose a method based on a predictive maintenance simulation model (PdMSM) for the above problem. The methodology for developing and validating SD models is based on the methods proposed by Bossel (2004), Sterman (2000) and Forrester (2013). In addition, the online documentation of AnyLogic provides methods and best practices to implement the model and a particular user interface that allows configuring different scenarios. Using this methodology, the following tasks should be carried out:

1) To propose the method that must be applied to identify the preferable workcenter for PdM application based on the simulation results.
2) To specify the model scope and considerations as a prerequisite for the development process.
3) To develop the simulation model including a user interface to perform parameter value-dependent experiments.
4) To verify the model.

In addition, the new knowledge is presented and discussed based on the application of PdMSM to real SI PS configuration data. The new knowledge is concerned with the confirmation of the hypothesis that benefits of PdM are not static, but dependent on particular scenarios. For instance, those situations in which PdM would reduce the production performance have been examined and discussed.

8.2 Proposition of a Method for the Model Application

The identification of the ideal workcenter for a PdM project requires several tasks beyond the execution of the simulation model. These tasks were identified during a design phase that was carried out prior to the model development. The goal of this design phase was to create a method that can be applied at any SI company in order to identify the workcenter where PdM shall be applied to gain significant SI PS performance improvements. Figure 8-1 shows the task sequence of this method.

The main challenge is to find a valid connection between workcenters and PS performance that allows effective investigation with minimum noise in the simulation. The more product lines are involved in a scenario, the more noise and lack of transparency are expected due to the product and process variety in SI PS. Therefore, this method requires the selection of one product line that is analysed against performance improvements when applying PdM to the involved workcenters. In this thesis, a high-volume product has been selected because a performance improvement would then generate the most significant and positive implications for the entire factory. As soon as the product is selected, different types of data must be gathered in order to initialise the simulation model. The model requires master data for workcenters and logistics, historical performance data, and soft information from expert assessment. Next, operations from the product route are selected that are compared with regard to performance improvement. These operations are the link to the workcenters that are affected by the application of PdM. The selection of operations must be performed based on expert advice; however, Section 8.7 presents some considerations for selection that have been identified through various experiments. Prior to the experiments and evaluations, the company must be clear about the goals they want to achieve by applying PdM. There are multiple KPIs as discussed in Chapter 4 with different audiences and objectives. For instance, the FF of the entire product line may be improved or only the yield of the some selected operations. Another goal could be the reduction of costs. The simulation generates results for all KPIs, however, it is not expected that all KPIs improve at the same level. To reduce the later efforts for analysis, evaluation and comparison, the goals are set beforehand.

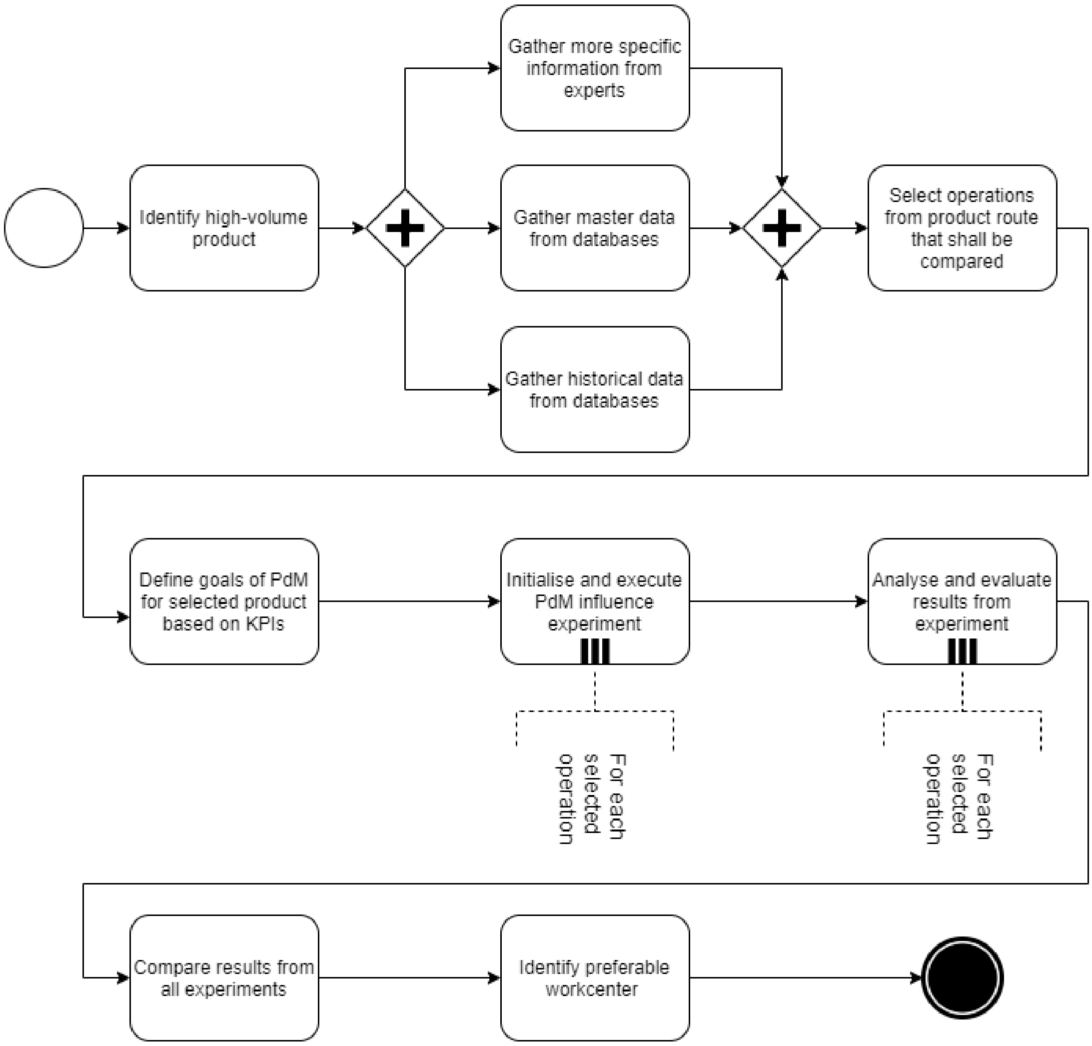


Figure 8-1: Proposed Method for applying PdMSM

Once these prerequisites are accomplished, the experiments can be performed using PdMSM. Each selected operation requires the execution of one experiment. Afterwards, the simulated results can be analysed and evaluated per experiment. The evaluation reveals the influences of PdM application on the selected KPIs for each operation. The degree of influences of PdM on KPIs can be compared between all selected operations. With the results from the comparison, a company can identify the preferable workcenter where a PdM project shall be initiated. Due to the looping processes that are required for adding multiple lithographic layers to a wafer (see 5.4), the same workcenters are likely to be used by different operations within a production route. Hence, it is suggested to execute the PdMSM for all operations that use the same machines. The single results can be merged afterwards in order to gain the full picture of influences of the application of PdM at a particular workcenter on the PS performances for the whole production route.

8.3 Model Scope and Considerations

According to Keating (1999), a common issue in projects that apply the SD methodology is the insufficiently designed model scope and specification. Important factors to consider when building a SD model are the problem definition, boundary adequacy, the time horizon, the selection of the appropriate time step *dt*, the selected type of aggregation, the selected integration method and the usage of noise variables (Keating, 1999). In order to overcome these factors, this section discusses the model scope and specification for the new simulation model as part of this thesis.

8.3.1 Problem Definition

The problem definition is important in order to state the purpose of the model, and subsequently, the simulation goal, precisely. It must be clear which problem is addressed, who the audience is for the results of the study, what the policies one wishes to experiment with are, and how shall it be implemented (Richardson and Pugh, 1988). As responded by the EM experts who participated in the PdM prototype project, the implementation of a PdM application that predicts specific failures for single machine types means a significant effort to EM engineers and data scientists. It is not realistic to expect that a company could apply PdM to all workcenters simultaneously because of limited human resources who require in-depth knowledge about processes, machines, data management and data analytics. Therefore, it would be useful for production managers – the audience – to know which workcenters would generate the largest PS performance improvement if they would be managed through PdM. The goal of this simulation model is to identify and quantify influences of the application of PdM on the various characteristics of PS performance over time. For practical application, PdMSM will support production managers to select the workcenter where the application of PdM would generate the largest benefit for PS performance under consideration of workcenter-, operation- and product-line-specific aspects. The model audience can experiment with policies as they can select different operations to be analysed for performance improvements. They can further change the weights of influences between model variables to generate a range from rather optimistic to rather pessimistic results. The simulation model shall visualize a trend how single performance indictors would evolve within the concrete PS when applying PdM to a specific workcenter. The simulated trends of multiple workcenters can be compared to identify the best one. The simulation model is partitioned into different sub-models where each consists of variables that are related through a common subject, e.g., costs or operation. Despite this design decision, relations between variables from different sub-models can be created without any loss of functionality. For a potential user, it is much easier to view and understand details of the model and therefore to modify parameters compared to one comprehensive model such as the CLM from Chapter 6. The simulation frame acts as the entry point for the users to configure a simulation scenario. AnyLogic provides the feature of ‘shadow variables’ that are associated to a real variable. Shadow variables can be used in any sub-model without the necessity of creating redundant instances of the same variable (AnyLogic, n.d.-a).

As specified by the method, the model focuses on a standard high-volume production route. The model calculates the impacts of PdM applications on a specific high-volume production route. If a company uses the model, an engineer must enter the concrete characteristics of a real production flow as model parameter values. In Section 8.6, the model is validated against several test procedures.

8.3.2 Boundary Adequacy

To define the system boundary, Richardson and Pugh (1988) pointed out that the modeller must include all concepts and variables in order to relate significantly to the dynamics of the problem being addressed. To identify the mandatory elements, it is proposed to include the ones that are directly or transitively influenced by PdM. This information was gained during the evaluation of PPES. Terms can be ignored for the simulation model when they only participate on impact associations as targets and are not directly or transitively affected by the application of PdM. The existence of the terms in the simulation model does not generate deeper understandings regarding impacts of PA on manufacturing performance. Because they are only target terms, they do not affect any other PS element. In addition, they are not affected by PdM in any logical way, therefore the simulation would not provide any new insight. Finally, ten terms can be excluded from the simulation model as listed in Table 8-1. The numbers refer to the unique key that was generated during the raw data analysis.

Table 8-1: Out-of-Scope Terms for the Simulation Model

#	**Term**
43	Engineering Time Duration
56	Scheduled Down Duration
69	Deliverability
91	Importance Of EM Availability
92	Importance Of Equipment Availability
93	Importance Of Operator Qualification Level
104	MTTF
121	Risk Of Equipment Bottleneck
122	Risk Of Product Line Down

Although the model connects multiple PS elements, it is not considered to support other production-relevant decision processes. Examples for out-of-scope processes include the evaluation impacts of WSPW modifications on the WIP variance, or the evaluation of impacts of an additional machine on the GR.

8.3.3 Time Horizon and Time Step

According to Forrester (1973), the time horizon of the model needs to be related to the concrete issue under study as well as the decisions being considered. The issue under study is a SI PS with business-specific challenges. These challenges may be unpredictable product differentiations, complex machines, high quality processes and related information. These challenges change continuously due to rather short product lifecycles compared to other industries such as the automotive industry (Forster et al., 2013). Because of these considerations, the time horizon must not be too large otherwise, the simulated KPI trends may not be meaningful in a later period. The objective is to detect the preferred workcenter that should be selected for a PdM application. Based on the recorded effects in the CLM, it is expected that the effects of PdM application on the PS performance would appear with some delay after the application is released. However, it is not realistic to assume that the simulated PS performance trend, which was triggered by a single workcenter, would significantly change over more than one year. Based on this discussion, the simulation scenario was configured to analyse a SI PS over one year. This time horizon has been used to execute experiments and to validate the model; nevertheless, a user of the model is able to change the time horizon.

The time step *dt* must be determined in accordance with the configured time horizon. Kampmann (1991) highlighted that if *dt* is too large, it may introduce an implicit delay in feedback. According to Forrester (2013), a too large a value for *dt* might lead to integration errors, which can be detected by observing rapid changes in variables that disappear after *dt* is decreased. Professional software such as AnyLogic supports modellers by configuring the time step automatically. A number of accuracies must be set, such as the time accuracy and a relative accuracy, which influences the implicit selection of the time step by the tool. To view the actual time step that is used by the simulation engine, the following statement can be executed during the runtime, for instance as part of a dynamic variable:

```
getEngine().getNextStepTime()-time()
```

However, it is important to select an appropriate time unit and to use it as the base unit for all values of the model. Based on the extracted data from the case study, using ‘week’ as the time unit is suggested because the influences of PdM would not significantly change within one day. For model elements such as the RPT that refers to an hour-based value, the model time unit must be considered within the according equations.

8.3.4 Methods for Differential Calculus

AnyLogic provides two numerical methods for differential equations: Euler and RK4, which is an abbreviation for the 4th order Runge-Kutta. In general, the Euler method is a simple computational technique that performs fast in simulation software tools. RK4 is the preferred method for models that are concerned with oscillations (Keating, 1999). When applying the Euler method, stock variables are calculated at the beginning of a time interval and stay constant during the time step *dt*. This leads to approximation errors that can be reduced by decreasing *dt*. However, if the time step becomes too small, other numerical inaccuracies may appear that distort the simulation result. The RK4 method is more accurate but requires more resources for computation, and therefore, performs more slowly. The primary difference to the Euler method is that stock variables do not remain constant during a time step. The RK4 method uses four points in time within the configured time step interval to calculate a stock variable. At the end of the time step, the intermediate results per stock variable are totalled and the model time is increased by *dt*. The correct selection of the integration method must be tested against the model results. If no unacceptable difference is detected, the Euler method can be applied, as a general rule (Fleissner, 2005).

8.3.5 Type of Aggregation

The type of aggregation of model elements must be clear and valid. Senge and Forrester (1980) suggested aggregating phenomena together, which have a similar dynamic behaviour or underlying dynamic structures. However, phenomena with different response times may not be mixed together. They also highlight that the model purpose determines which level of aggregation is appropriate. Rahmandad and Sterman (2018) described the impact of the purpose on the level of aggregation in more detail. When analysing, for instance, the obesity at a population level, the population can be represented via one highly aggregated stock variable. However, when different groups of people need to be distinguished (e.g., by weight), it would be more appropriate to define one stock variable per population group. The most detailed level would be the single individual as part of the population.

Such an individual should not be represented as stock variable but as agent, which is a technical concept within simulation software. The selected type of aggregation influences the selection of a simulation method. Aggregated elements are easier to represent via differential equations whereas less or even non-aggregated elements are better represented by agents.
Rahmandad and Sterman (2018) proposed the following considerations to choose an appropriate aggregation level:

- The level of aggregation of an element in the model must conform to the level of aggregation in the available data. If the model component disaggregates below the data source, auxiliary and parameter assumptions would be required that are hard to justify. Aggregating above the level of aggregation in the data might discard useful information; however, this information can be ignored if those details are not relevant for the model purpose.
- To facilitate a seamless integration of different model components, the level of aggregation between model components should be similar. The similarity fosters the ease of maintenance of the internal model consistency.
- Disaggregating requires more detailed data and this leads to higher effort for data collection, analysis, new mechanisms and related activities. To keep the balance between the level of detail, quality of prediction and reasonable effort, a modeller should focus on those model components that add the most value to the project.

Because the purpose of the model is to identify and quantify influences of a PdM application on the PS performance based on the performance changes of several selected workcenters, the model component ‘workcenter’ will act as basis to align the level of aggregation with other model components. The level of aggregation of ‘workcenter’ refers to a group of physical production machines that are redundant for a specific operation within a production route. In addition, the historical data from the case study supports the selection of this level of aggregation because the extracted TR25 availability records are also aggregated by workcenter. As observed from the equipment master data, production machines that are grouped by the same workcenter are mainly identical in construction (e.g., same equipment manufacturer and same equipment platform). Therefore, it is expected that the failure patterns and preventive methods are valid for all machines within a common workcenter. With regards to the dynamics of the model, it must be considered that effects of a PdM application on a workcenter are delayed dependent on the number of machines that must be considered.

8.3.6 Noise

Beyond the previously discussed specifications, a SD modeller must consider the noise in a system. Forrester highlights that an understanding of noise is essential in working with models of information feedback systems. Noise is a trigger for those disturbances to which a system is sensitive and limits the ability of proper predictions. The future of a system under study can be by unexplained factors. Noise may have influence on the decision functions within the model and on the results. Two types of noise can be identified in general (Forrester, 2013):

a) The first type of noise refers to slight influences from variables that are part of the model. This type of noise is the result of eliminating some of the feedback paths between the model variables. Consequently, some of the model variables are not considered by decision functions, though the variable value changes might correlate in time with the decisions created by the decision functions. The reason for this type of noise is the necessity for simplification. This type of noise cannot be substituted by random variables.
b) The second type of noise means factors that are not themselves affected by each other or by the other variables of the model. Their source (e.g., the weather) is outside of and independent of the system being represented. In principle, this type of noise can be approximated by random variables as input to a decision function. However, it depends on the knowledge of the system under study whether the proper and sufficient noise variables can be identified and added.

Because the SI PS as the system under study is a physically isolated environment within a controlled cleanroom, the weather and similar external effects are not regarded as crucial to the prediction quality. Other external factors that influence the PS execution, such as the delay in delivery of raw material, or loss of operator availability due to the flu season, could be substituted by random variables. A crucial factor that generates effects from the second type of noise is the deviation in the material flow. To cover these deviations that affect the PS performance, the model uses a statistic function. By contrast, effects from the first type of noise can have more significant influence on the decisions within the model. It is likely that the interviewed experts did not mention all logical associations that exist in reality, and thus, some model variables may not be considered sufficiently in decision functions. Furthermore, by aggregating physically independent system elements, some individual nuances are smoothed and their particular effect cannot be considered within decision functions.

8.4 Transforming Terms into SD Variables

SD models require the definition of types per system element. Similar to the PPES development, the terms from the CLM must be transformed into adequate variables to meet the requirements of SD simulation. Another option would be the transformation of PPES concepts into SD variables. However, it needs to be considered that the impact values are only available on term level. Because one term can be expressed by multiple concepts, there is partially no quantified association available between single concepts that are associated through object properties. Without the existence of a weighted association, the single concept will not add any insights during the simulation. Only the FOL representations from Section 7.6, where the single PPES concepts are associated with original terms, could be used to assign the original impact value information. Nevertheless, it would result in the same level of information – the original terms – but with additional complexity in the model design. Because of missing benefits and the chance to achieve a much clearer model design, the initial terms were selected. The link between terms, PPES elements and SD variables is ever present because the thesis refers consistently to the unique term ID.

Forrester (2013) and Bossel (2004) define categories for model elements that are described as follows:

1) **Initial variables**: These represent the exogenous influences from the outer environment on the particular system. These impact factors are independent and cannot be altered by model elements during a simulation run. They can be modelled either as constant or as formula.
2) **Stock variables**: At each point in time, stock variables return the state of the particular system. Their value cannot be derived from other system elements, and thus, they are irreplaceable. Stock variables are mathematically modelled as integral to corresponding flow equations. Depending on the literature, they are also known as state variables or levels.
3) **Auxiliary variables**: The values of auxiliary variables are calculated from stock variables or initial variables. They can also be subdivisions of flow equations to reduce the complexity of functions. Auxiliary variable equations consist of algebraic and logical functions. During a simulation run, the simulation engine evaluates auxiliary variables after stock variables but before flow equations per time step.
4) **Supplementary variables**: These are not relevant to the simulation model itself but used as aggregated information to summarize the results of a simulation scenario.
5) **Flows**: Flows contain the decision functions that control what happens next in the system. They may refer to values of source and target stock variables. Flow equations are independent of one another. Initial and auxiliary variables only influence a specific stock variable if they are included in the related flow equation.

Due to the calculus as the mathematical foundation of SD, stock variables and flows have a specific dependency. A flow equation represents the first derivative of a stock variable between two points in time. As described by Forrester (2013) and Bossel (2004), the mathematic functions that express the impact associations between system elements are dependent on the SD element type.

A high percentage of the terms can be directly assigned to a variable category. For instance, ‘Number of Failures’ meets the criteria of a stock variable, whereas ‘FF’ can be modelled as an auxiliary variable. However, there are terms such as ‘Degree of Exhausting Wear Limits’ that rather meet the criteria of an auxiliary variable but without a related stock variable where the information can be derived. For such cases, new model elements must be added. These elements allow deeper design of a logical background for an auxiliary variable, and therefore, enable a proper and transparent mathematic calculation. The 'Degree of Exhausting Wear Limits' can then be calculated based on a new stock variable that counts the number or spare part replacements over time. Stock variables can be grouped together as part of a sub-model. A sub-model depicts a specific area or perspective from the overall system under study. Other model components such as flows and auxiliary variables are also part of the sub-model where the corresponding stock variable is located.

Terms require special treatment to generate consistent equations if they are targets in the CLM and characterized as KPI based on the discussion of Section 4.3. Because the experts are used to expressing the PS performance through KPIs, it was important to document their expectations of how these KPIs would be influenced by PS or PdM characteristics. However, a KPI is already based on a formula, so it could lead to inconsistencies in the simulation result if additional equations were created for the same variable. In this thesis, three approaches are identified to handle these cases:

A) The documented impact is applied to the physical root elements of the KPI formula instead of the KPI itself.
B) The documented impact is applied to the KPI equation result.
C) The documented impact is applied to the KPI formula.

To support the decision, the pro and contra arguments for each approach must be collected and compared. Table 8-2 lists the identified arguments.

The evaluation and comparison of each argument leads to the decision to go for Approach A. This approach combines the most positive arguments with the least effective negative argument. Though the initial intention of the expert would be hidden in the simulation model, the documented effect must be still valid and identical based on the mathematical association within a KPI equation. Each impact association that consists of a KPI as a target term must be modified. The documented association will be redirected to the appropriate root element of the particular formula. A root element is appropriate, if its growth or reduction influences the KPI value by the same factor as mentioned by the initial impact association.

Table 8-2: Comparison of Approaches to treat Impact Associations between a Source Term and a KPI as a Target Term

Approach	Pro	Contra
A	• The well-defined KPI formula will not change, and thus, the equations do not differ from literature. • The calculated result value of a KPI is only based on the underlying formula from literature and not modified through a second calculation. • From a logical point of view, it is more likely that root elements of KPI formulas are influenced by a PS element than the KPI value itself, without changing a root element's value.	• The intention of the experts who mentioned this particular impact association is not clear, and thus, the researcher could potentially misrepresent the impact association.
B	• The statement of the experts who mentioned this particular impact association remains. • The well-defined KPI formula will not change, and thus, the equations do not differ from literature.	• The calculated result value of a KPI depends on two separated formulas. This makes the calculation inconsistent compared to equations from literature. • Each influenced KPI is represented by two variables in the simulation model. This type of doubling would inflate the model and reduce the transparency for analysis purposes.
C	• The statement of the experts who mentioned this particular impact association remains. • Only one variable and equation are required to specify a KPI result value.	• The well-defined KPI formula is modified, and thus, the equations differ from literature. This modification reduces the applicability of the simulation model for real environments.

The transformation is demonstrated by the following example:

PdM Application increase GR by 6.55

Based on Equation (4.14) that represents the formula of GR, the fabricated items n^{actual} are the appropriate root element that is influenced by the application of PdM instead of GR. The value of GR would change in the same way regardless of whether the impact value of PdM Application, which is 6.55, would be multiplied to n^{actual} or to GR directly. With this approach, the documented impact of PdM Application on GR remains; the equation for GR is still the same as in the literature and the simulation model does not require doubled variables. In cases where the KPI formula refers only to other KPIs as root elements (e.g., FF, which is based on CT), the appropriate root element in the formula of the ingoing KPI is searched. This procedure is repeated until the appropriate root element is identified in a source formula.

The selected approach works only for algebraic equations, but cannot be applied to statistical dispersions of PS parameters or KPIs, such as WIP variance, WSPW variance or all types of Alpha. For example, the variance of a random variable *X* is the expected value of the squared deviation from the mean of *X*. The mathematical foundation does not allow the direct combination of impact associations and statistical dispersions. To ensure a consistent and trusted simulation, all impact associations from the simulation model that consider statistical dispersions as either source or target are removed. The logical effects of those associations are visible in the PPES, thus, the information is available for production managers in addition to the quantified simulation results.

8.5 Model Development

The following sub-sections discuss the development of the simulation model, which consists of six sub-models as shown in Figure 8-2.

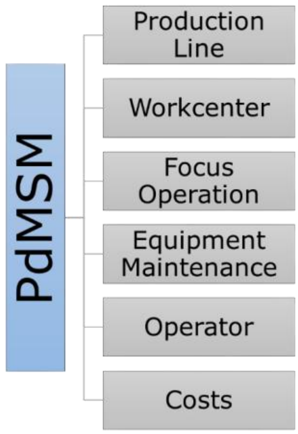


Figure 8-2: Structure of the PdMSM

Each sub-section presents one sub-model including its general structure, model elements as well as stock and flow equations. The equations for auxiliary variables are listed in appendix A3. The final sub-section presents the development of the simulation frame that an end-user would access to initialise and modify simulation scenarios.

8.5.1 Production Line Sub-Model

8.5.1.1 General Model Structure

Most of the PS-oriented KPIs depend on the flow of items through the production line, whose characteristics are set in relation to the according planning values. For instance, to calculate the GR for a product within a defined period, the number of items that pass a logistic unit per time unit must be measured. Such a logistic unit can be an operation, a group of operations or the entire production route – the actual selection depends on the required level of detail. In any case, the simulation model must contain the production flow as a basic component to simulate the flow of items and to calculate PS-oriented KPI values. The thesis selects the 'production route', which refers to a particular product, as an appropriate level of detail for the simulation scenario. The main reason for this decision is that PS performance as a whole shall be represented as stated by the thesis goal. Therefore, it is not sufficient to focus on single operations only. The production line sub-model is a logical connection point between other sub-models whose variables influence the flow of items, such as equipment availability and yield. It represents the characteristics and dynamics of a particular production route that must be parameterized by the model user before starting the simulation. It sets the focus on a particular operation that is part of the production route plan. This operation is called 'focus operation' within this thesis. There is a generic pre-process as well as a generic post-process that works with aggregated average values that must be set based on real historical data. The flows between the stock variables represent the flow of items along the production line.

The number of operations within the focus production route must be used to weight the performance values of the focus operation correctly in relation to the performance values of all other operations. The focus operation refers to a defined group of machines and EM activities that are particularly improved by PdM within a simulation run. These improvements are expected to affect the logistic performance of the focus operation. To simulate the degree of performance improvement for the entire production route, the performance of the other operations must be considered as well. For this purpose, the generic pre-process and post-process are required. Figure 8-3 shows the relation of the production line sub-model to a real production route and how two operations from the same route can be compared.

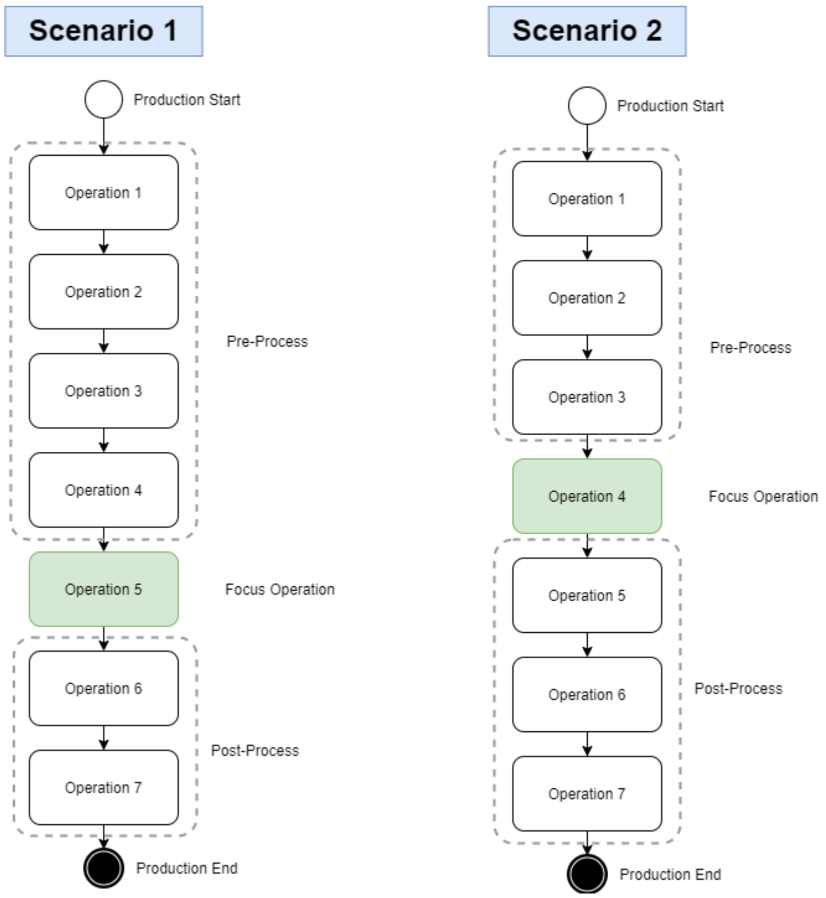


Figure 8-3: Relation of the Production Line Sub-model to a Real Production Route

The figure shows two different simulation scenarios for the same production route that consists of seven operations in sequence. In scenario 1, ‘Operation 5’ is configured as focus operation whereas in scenario 2 it is ‘Operation 4’.Both pre-process and post-process are groupings of operations. Per simulation run, one operation from a route is selected as the focus operation. This selected operation is excluded from the considerations of pre-process and post-process. With this approach, it is possible to compare multiple operations from a route to find out which one would generate the highest performance improvements for the overall production line when PdM is applied.

Figure 8-4 shows the developed production line sub-model that implements the previously discussed approach.

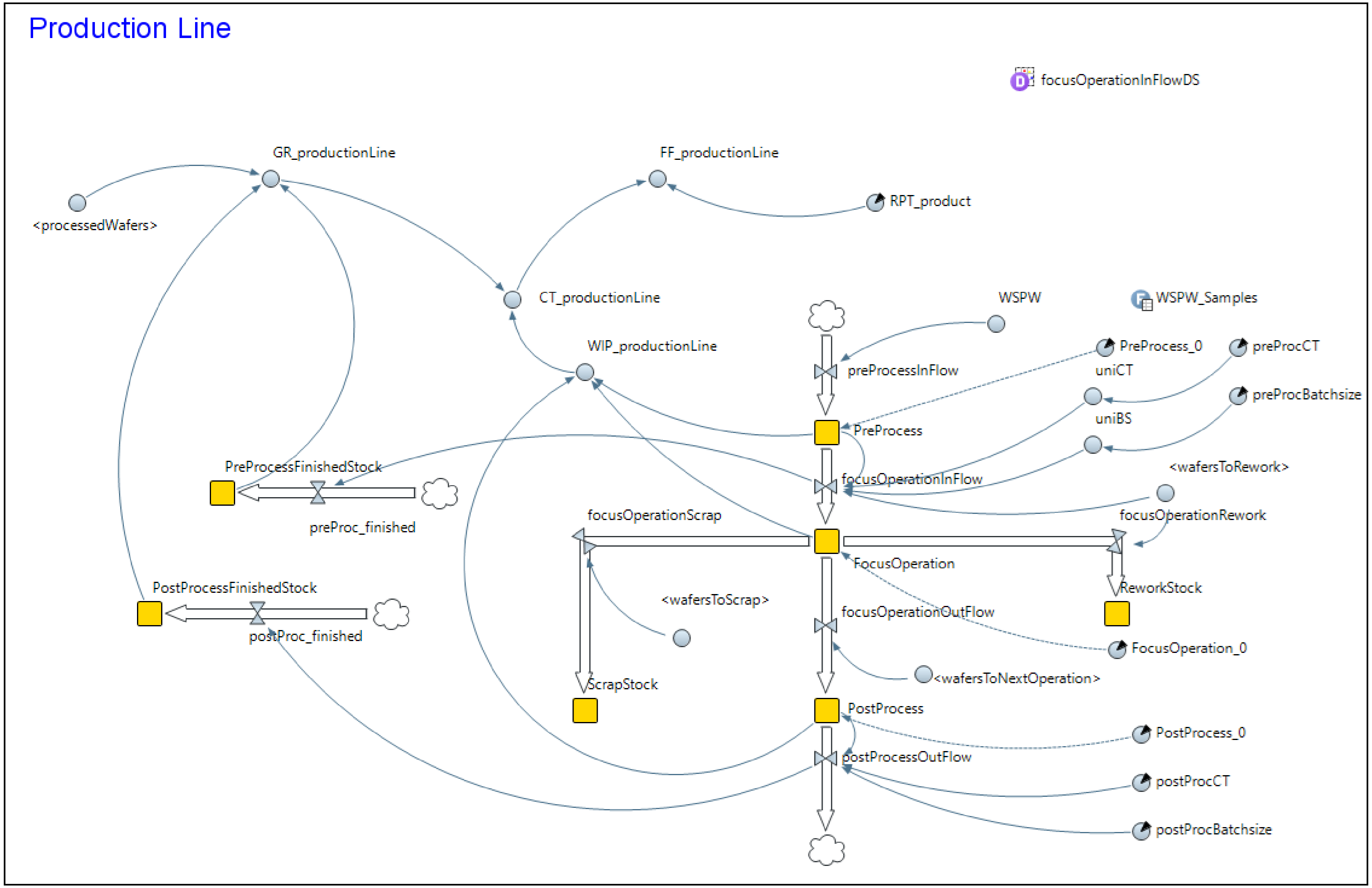


Figure 8-4: Production Line Sub-Model

The sub-model consists of following stock variables that are represented as a gold-coloured rectangle and that interact with other model elements:

- PreProcess
- FocusOperation
- PostProcess
- ScrapStock
- PostProcessFinishedStock
- PreProcessFinishedStock

8.5.1.2 Model Elements and Equations

The sub-model requires several input parameters that must be configured prior to the simulation execution. Table 8-3 lists and describes those parameters.

Table 8-3: Parameters for Production Line Sub-Model

Parameter	Unit	Description
RPT_product	Week	The raw process time for the whole product including all operations.
preProcCT	Week	The average cycle time for the set of operations prior to the focus operation.
preProcBS	Number of Wafers / Operation	The average batch size for the set of operations prior to the focus operation.
postProcCT	Week	The average cycle time for the set of operations that follow the focus operation.
postProcBS	Number of Wafers / Operation	The average batch size for the set of operations that follow the focus operation.
PreProcess_0	Number of Wafers	Initial stock value that refers to the sum of WIP of all pre-processes.
PostProcess_0	Number of Wafers	Initial stock value that refers to the sum of WIP of all post-processes.
FocusOperation_0	Number of Wafers	Initial stock value that refers to the WIP at the focus operation.

The stock variable ‘PreProcess’ counts the number of items that are currently in progress at any operation prior to the focus operation. The variable ‘preProcessInFlow’ is only influenced by the WSPW that indicates how many wafers will enter the factory for this particular product within the defined period. The variable ‘focusOperationInFlow’ represents the number of items that are moved from the pre-process group to the focus operation within the defined period. Because the simulation can start at any time during the lifetime of a PS, the stock variable must be assigned to an initial value ‘$PreProcess_0$’. This value represents the current WIP of all operations prior to the focus operation. Equation (8.1) defines the how the stock variable ‘PreProcess’ is calculated.

$$PreProcess = PreProcess_0 + \int_0^t (\mathrm{preProcessInFlow} - \mathrm{focusOperationInFlow}) * \mathrm{dt} \tag{8.1}$$

Unit: Item

From the case study data, it is known that the WSPW is not a static value but fluctuates per week. AnyLogic provides a function component called ‘Table Function’ that allows the storage of sample data to be used for simulation. An instance of this component is added to the model and named ‘WSPW_Samples’. It consists of 53 records where each consists of a pair of ID and value. The ID refers to the current week within the simulation time and the value to the historical WSPW data. The 53rd record is only required to avoid null pointer exceptions during the simulation and has ‘0’ as value. The dynamic variable ‘WSPW’ accesses the sample data using Equation (8.2).

$$WSPW = WSPW\_Samples(round(time())) \tag{8.2}$$

Unit: Item

The flow variable ‘preProcessInFlow’ is only influenced by ‘WSPW’ and is calculated by Equation (8.3).

$$preProcessInFlow = WSPW \tag{8.3}$$

Unit: Item

The next stock element within the production line flow is the *FocusOperation*. It is defined by Equation (8.4) that covers one ingoing and two outgoing flows.

$$\begin{aligned} FocusOperation = {} & FocusOperation_0 \\ & + \int_0^t (\mathrm{focusOperationInFlow} - \mathrm{focusOperationOutFlow} \\ & - \mathrm{focusOperationScrap}) * \mathrm{dt} \end{aligned} \tag{8.4}$$

Unit: Item

The ingoing flow depends on the current stock of all the pre-processes, the average cycle time of all pre-processes and the average batch size of all pre-processes as well as the number of wafers that are selected for rework. Wafers to rework having already passed the focus operation have to be processed again due to quality issues. The flow is physically limited by CT and the batch size of the pre-processes and, in case this rate increases the stock, the *PreProcess* itself to avoid negative stock values. Equation (8.5) shows the flow definition.

$$focusOperationInFlow = limitMax\left(\left(\frac{1}{uniCT}\right) * uniBS, PreProcess\right) + wafersToRework \quad (8.5)$$

Unit: Item

The stock variable consists of two outgoing flows, one for the good wafers that are sent to the next operation and one for the scrapped wafers that are removed from the production line. The outgoing flows are defined by Equation (8.6) and (8.7).

$$\mathrm{focusOperationOutFlow} = \mathrm{wafersToNextOperation} \quad (8.6)$$

Unit: Item

$$\mathrm{focusOperationScrap} = \mathrm{wafersToScrap} \quad (8.7)$$

Unit: Item

Both variables *wafersToScrap* and *wafersToNextOperation* are filled within the operation sub-model that is described in 8.5.3. The good wafers are passed to the stock *PostProcess* that is defined by Equation (8.8).

$$PostProcess = PostProcess_0 + \int_0^t (\mathrm{focusOperationOutFlow} - \mathrm{postProcessOutFlow}) * \mathrm{dt} \quad (8.8)$$

Unit: Item

The initial value *$PostProcess_0$* stands for the sum of WIP for all operations that follow on the *FocusOperation* over the production line for the selected route. The stock is modified by the ingoing flow *focusOperationOutFlow* and the outgoing flow *postProcessOutFlow*, which is also the final part of the overall production line flow. The outgoing flow is defined by Equation (8.9).

$$postProcessOutFlow = limitMax\left(\left(\frac{1}{postProcCT}\right) * postProcBatchsize, PostProcess\right) \tag{8.9}$$

Unit: Item

Similar to the *focusOperationInFlow*, the flow is physically limited either by the average CT and average batch size of all operations that follow the focus operation or by the *PostProcess* itself. The last stock variable within the direct production line flow is the *ScrapStock*, which stores all wafers that did not pass the focus operation. Subsequently, it does not consist of an outgoing flow. It is defined by Equation (8.10).

$$ScrapStock = ScrapStock_0 + \int_0^t (\text{focusOperationScrap}) * \text{dt} \tag{8.10}$$

Unit: Item

To calculate the KPIs for the whole production line, it is also necessary to store the number of wafers that were processed by the pre- and post-operations. For this purpose, the sub-model consists of two stock variables *PreProcessFinishedStock* and *PostProcessFinishedStock* that are defined by Equations (8.11) and (8.12).

$$PreProcessFinishedStock = PreProcessFinishedStock_{\,0} + \int_0^t (\text{preProc\_finished}) * \text{dt} \tag{8.11}$$

Unit: Item

$$PostProcessFinishedStock = PostProcessFinishedStock_{\,0} + \int_0^t (\text{postProc\_finished}) * \text{dt} \tag{8.12}$$

Unit: Item

Both stock variables only consist of ingoing flows that obtain their values directly from the outgoing flows from *PreProcess* and *PostProcess*. Due to this triviality, the equations are not shown in detail.

The sub-model also consists of KPIs that express the performance of the whole production line. These KPIs are defined by algebraic equations.

Equation (8.13) shows the calculation of the GR that depends on the different finished stocks for pre-processes, focus operation and post-processes. The variable *processedWafers* refers to the focus operation and is filled within the operation sub-model.

$$GR_{productionLine} = \frac{\mathrm{PreProcessFinishedStock} + \mathrm{PostProcessFinishedStock} + \mathrm{processedWafers}}{\mathrm{time()}} \quad (8.13)$$

Unit: Item

The current WIP of the whole production line is calculated by Equation (8.14).

$$WIP_{productionLine} = \mathrm{PreProcess} + \mathrm{FocusOperation} + \mathrm{PostProcess} \quad (8.14)$$

Unit: Item

With WIP and GR, the CT can be calculated for this scenario by Equation (8.15).

$$CT_{productionLine} = \frac{\mathrm{WIP_{productionLine}}}{\mathrm{GR_{productionLine}}} \quad (8.15)$$

Unit: Time

Finally, the CT can be compared with the RPT for the selected product to calculate the FF as defined by Equation (8.16).

$$FF_{productionLine} = \frac{\mathrm{CT_{productionLine}}}{\mathrm{RPT_{product}}} \quad (8.16)$$

Unit: N/A (Factor)

8.5.2 Workcenter Sub-Model

8.5.2.1 General Model Structure

The workcenter sub-model that is depicted in Figure 8-5 consolidates all variables that are directly related to equipment-oriented stock variables.

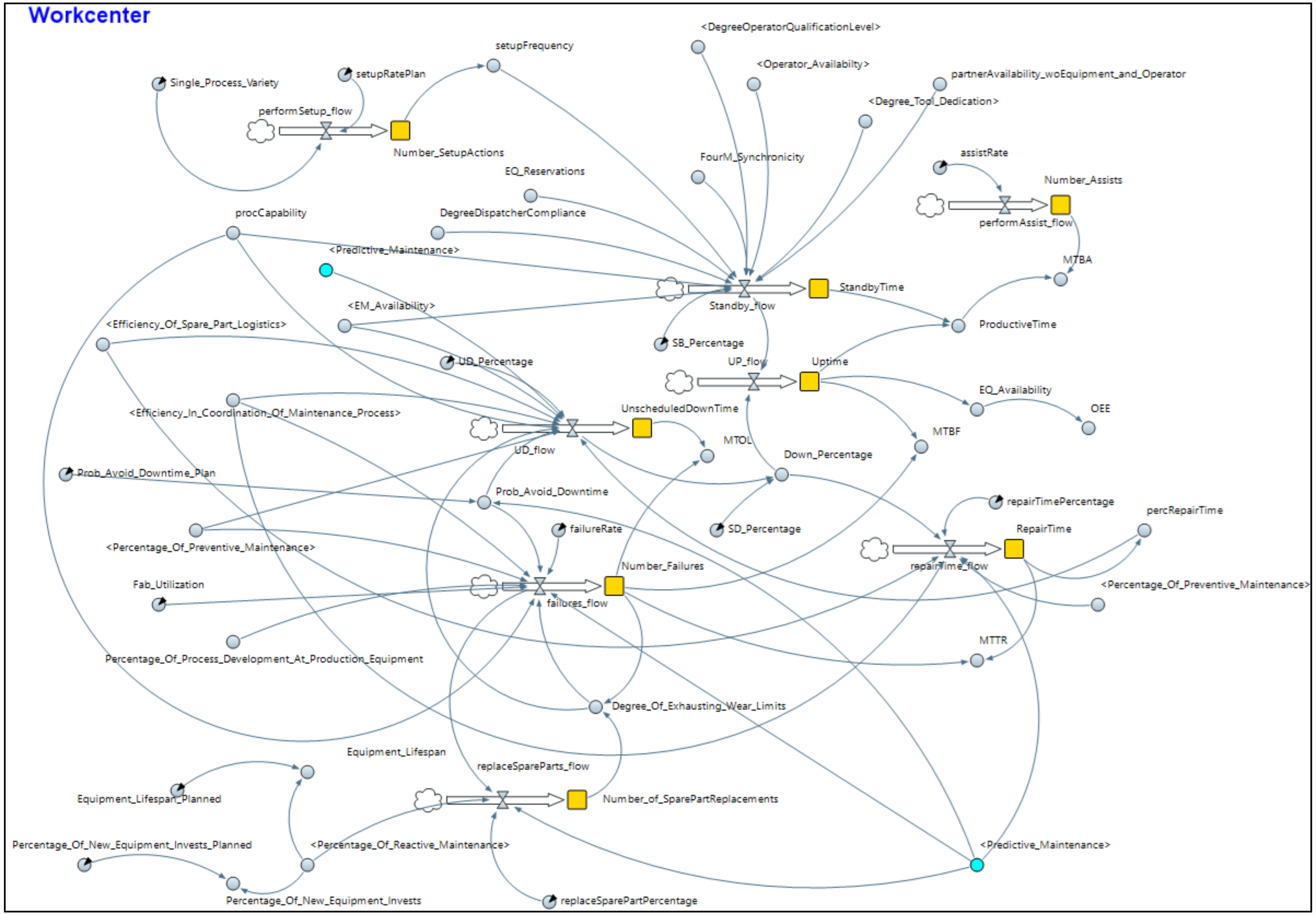


Figure 8-5: Workcenter Sub-Model

It mainly contains machine-oriented KPIs from Section 4.4 whose calculation follows the described formulas. The sub-model is able to store the sum of different equipment times (e.g., uptime, unscheduled downtime) over the simulation horizon. It is possible to evaluate the impacts of PdM on the machine performance by comparing the final values of the stock variables from the two scenarios: normal execution of the SI PS and execution after application of PdM at the focus operation. Furthermore, it is possible to compare the trend charts of the machine-oriented KPIs between these two simulation scenarios.

The sub-model consists of the following stock variables (gold-coloured in the sub-model) that interact with other model elements:

- Uptime
- UnscheduledDownTime
- StandbyTime
- RepairTime
- Number_Assists
- Number_Failures
- Number_of_SparePartReplacements
- Number_SetupActions

8.5.2.2 Model Elements and Equations

The sub-model requires a set of parameters as input for the equations. Table 8-4 explains the meaning and unit of these variables.

The core of the model is to obtain failures and unscheduled downtimes. These result values influence the majority of the other sub-model components. The stock variable *UnscheduledDowntime* is defined by Equation (8.17).

$$UnscheduledDowntime = UnscheduledDowntime_0 + \int_0^t (\mathrm{UD\_flow}) * \mathrm{dt} \tag{8.17}$$

Unit: Weeks

The corresponding flow *UD_flow* that increases the unscheduled downtime over the simulation horizon is influenced by several factors. An average unscheduled downtime must be preconfigured based on empirical insights. Based on the associations from the CLM, this percentage can change during a selected timeframe. Equation (8.18) shows these mathematical relations.

$$\begin{aligned} UD\_flow = {} & UD\_Percentage - UD\_Percentage * 7.5 * ImpactFactor \\ & * Degree\_Of\_Exhausting\_Wear\_Limits - UD\_Percentage * 7.5 \\ & * ImpactFactor * ((MTTR\_Plan - MTTR) * 100) \\ & - UD\_Percentage * 5 * ImpactFactor * (Prob\_Avoid\_Downtime) \\ & - UD\_Percentage * 8 * ImpactFactor \\ & * (Efficiency\_In\_Coordination\_Of\_Maintenance\_Process) \\ & - UD\_Percentage * 7 * ImpactFactor \\ & * (Percentage\_Of\_Preventive\_Maintenance) - UD\_Percentage \\ & * 4.5 * ImpactFactor * (EM\_Availability) - UD\_Percentage * 7 \\ & * ImpactFactor * (Efficiency\_Of\_Spare\_Part\_Logistics) \\ & - UD\_Percentage * 2 * ImpactFactor * processCapability \\ & - UD\_Percentage * 1 * ImpactFactor * Predictive\_Maintenance \end{aligned} \tag{8.18}$$

Unit: Percentage / Week

Table 8-4: Parameters for the Machine Sub-Model

Parameter	Unit	Description
UD_Percentage	Percentage [0-1] / Day	Represents the average percentage of unscheduled downtime per day of the workcenter that is assigned to the focus operation.
MTTR_Plan	Percentage [0-1] / Day	Represents the planned MTTR per day the workcenter that is assigned to the focus operation.
failureRate	Number of Failures / Day	Represents the average number of failures per day of the workcenter that is assigned to the focus operation.
SD_Percentage	Percentage [0-1] / Day	Represents the average percentage of scheduled downtime per day of the workcenter that is assigned to the focus operation.
assistRate	Number of Assist / Day	Represents the average number of assists per day of the workcenter that is assigned to the focus operation.
EQ_Reservations	Percentage [0-1] / Day	Represents the average percentage of equipment reservations for engineering purposes per day of the workcenter that is assigned to the focus operation.
repairTimePercentage	Percentage [0-1] / Downtime	Represents the average percentage of workcenter downtimes that is purely required for repair activities.
replaceSparePartPercentage	Percentage [0-1] / Downtime	Represents the average percentage of failures where spare parts must be replaced per day at the workcenter that is assigned to the focus operation.
Prob_Avoid_Downtime	Percentage [0-1]	Represents the probability to avoid downtimes per day at the workcenter that is assigned to the focus operation.

Similar to the unscheduled downtime, the number of failures over the simulation period is represented as stock variable. The variable is defined by Equation (8.19).

$$Number\_Failures = Number\_Failures_0 + \int_0^t (\text{failures\_flow}) * \text{dt} \tag{8.19}$$

Unit: Number of Failures

The flow *failure_flow* increases the number of failures continuously. An average number of failures per day, which is called *failureRate*, is the main driver for increase. It can be reduced or increased by several factors. Equation (8.20) describes the mathematical dependencies.

$$\begin{aligned} failure\_flow = failureRate - failureRate * 5 * \ ImpactFactor \\ * Degree\_Of\_Exhausting\_Wear\_Limits - failureRate * 5 \\ * ImpactFactor * (Prob\_Avoid\_Downtime) - failureRate * 5 \\ * ImpactFactor \\ * (Efficiency\_In\_Coordination\_Of\_Maintenance\_Process) \\ - failureRate * 9 * ImpactFactor \\ * (Percentage\_Of\_Preventive\_Maintenance) + failureRate * 7 \\ * ImpactFactor * Fab\_Utilization - failureRate * 5.83 * ImpactFactor \\ * processCapability + failureRate * 1.67 * ImpactFactor \\ * Percentage\_Of\_Process\_Development\_At\_Production\_Equipment \\ - failureRate * 7 * ImpactFactor * Predictive\_Maintenance \end{aligned} \tag{8.20}$$

Unit: Number of Failures / Week

Another crucial time indicator for workcenter evaluation is the standby time that is defined by Equation (8.21). The *SB_flow* that adds standby time to the stock only influences it.

$$StandbyTime = StandbyTime_0 + \int_0^t (\text{SB\_flow}) * \text{dt} \tag{8.21}$$

Unit: Weeks

The main driver for *SB_flow* is the *SB_Percentage,* which is an average percentage predefined by the simulation user. This percentage is influenced by several parameters as defined by Equation (8.22).

$$SB\_flow = SB\_Percentage - 6 * ImpactFactor * SB\_Percentage * EM\_Availability - 5.3 * ImpactFactor * SB\_Percentage * DegreeDispatcherCompliance - (FourM\_Synchronicity = = 1 ?\ 10 * ImpactFactor * SB\_Percentage :\ 0) + 5.5 * ImpactFactor * SB\_Percentage * Degree\_Tool\_Dedication - 3.2 * ImpactFactor * SB\_Percentage * Operator\_Availabilty - 6 * ImpactFactor * SB\_Percentage * DegreeOperatorQualificationLevel - 4 * ImpactFactor * SB\_Percentage * partnerAvailability\_woEquipment\_and\_Operator - 4.67 * ImpactFactor * SB\_Percentage * setupFrequency - 2 * ImpactFactor * SB\_Percentage * processCapability + 3.33 * ImpactFactor * EQ\_Reservations * SB\_Percentage \tag{8.22}$$

Unit: Percentage / Week

Active parts in the model are the generation of unscheduled downtimes and standby times. Subsequently, the uptime of a workcenter can be derived from these values. The stock variable *Uptime* is defined by Equation (8.23).

$$Uptime = Uptime_0 + \int_0^t (\mathrm{UP\_flow}) * \mathrm{dt} \tag{8.23}$$

Unit: Weeks

The flow *UP_flow* is defined by Equation (8.24) and shows the dependencies to the other types of equipment times.

$$UP\_flow = 1 - (\mathrm{Down\_Percentage} + \mathrm{Standby\_flow}) \tag{8.24}$$

Unit: Percentage / Week

In this equation, *Down_Percentage* is the dynamic sum of *UD_flow* and the parameter *SD_percentage*, which is predefined. The difference between uptime and standby time describes the productive time of the workcenter. It can be calculated from two stock elements and is configured as dynamic variable. The productive time is also required to calculate the *MTBA*. In addition, the KPI formula requires the number of assists that is configured as stock variable as defined by Equation (8.25).

$$Number\_Assists = Number\_Assists_0 + \int_0^t (\mathrm{performAssist\_flow}) * \mathrm{dt} \tag{8.25}$$

Unit: Number of Assists

Because the identified causal relationships do not contain any impact on the number of assists, the according flow equation only depends on a predefined *assistRate* as shown in Equation (8.26).

$$performAssist\_flow = \mathrm{assistRate} \tag{8.26}$$

Unit: Number of Assists / Week

A crucial goal of PdM is the reduction of the repair time in case of a machine failure. In the workcenter model, the *RepairTime* is a stock variable and defined by Equation (8.27).

$$RepairTime = RepairTime_0 + \int_0^t (\mathrm{repairTime\_flow}) * \mathrm{dt} \tag{8.27}$$

Unit: Weeks

Only one ingoing flow exists that adds repair time to the stock. It is called *repairTime_flow* and is defined by Equation (8.28). The flow is mainly driven by the overall downtime percentage – both scheduled and unscheduled – and a realistic average percentage of repair time from this downtime.

$$\begin{aligned} repairTime\_flow \; = {} & Down\_Percentage * repairTimePercentage - Down\_Percentage \\ & * repairTimePercentage * 6.67 * ImpactFactor \\ & * Efficiency\_In\_Coordination\_Of\_Maintenance\_Process \\ & - Down\_Percentage * repairTimePercentage * 5 * ImpactFactor \\ & * Percentage\_Of\_Preventive\_Maintenance - Down\_Percentage \\ & * repairTimePercentage * 8 * ImpactFactor \\ & * Efficiency\_Of\_Spare\_Part\_Logistics - Down\_Percentage \\ & * repairTimePercentage * 6.4 * ImpactFactor \\ & * Predictive\_Maintenance \end{aligned} \tag{8.28}$$

Unit: Percentage / Week

Another expected positive impact of PdM is on the degree of exhausting wear limits. To quantify this degree in a meaningful way, a stock variable is created that counts the spare part replacements over the simulation timeframe. Equation (8.29) shows the definition.

$$Number\_of\_SparePartReplacements = Number\_of\_SparePartReplacements_0 + \int_0^t (\text{replaceSpareParts\_flow}) * \text{dt} \tag{8.29}$$

Unit: Number of Replacements

The associated flow is based on an expected percentage of spare part replacements based on the current number of failures. This number can be reduced by the application of PdM but increases by the percentage of reactive maintenance. Equation (8.30) shows the dependencies.

$$\begin{aligned} replaceSpareParts\_flow &= replaceSparePartPercentage * failures\_flow + 8 \\ &* ImpactFactor * replaceSparePartPercentage \\ &* failures\_flow * Percentage\_Of\_Reactive\_Maintenance - 8.4 \\ &* ImpactFactor * replaceSparePartPercentage \\ &* failures\_flow * Predictive\_Maintenance \end{aligned} \tag{8.30}$$

Unit: Number of Replacements / Week

As shown in Equation (8.31), the degree of exhausting wear limits is defined as the relation between the number of failures and the necessity to replace spare parts. The lower the number of spare part replacements, the higher is the degree of exhausting wear limits.

$$Degree\_Of\_Exhausting\_Wear\_Limits = \text{Number\_Failures} > 0 \; ? \; 1 - \frac{Number\_of\_SparePartReplacements}{Number\_Failures} : 0 \tag{8.31}$$

The last stock variable in this sub-model stores the number of setup actions and is defined by Equation (8.32).

$$Number\_SetupActions = Number\_SetupActions_0 + \int_0^t (\text{performSetup\_flow}) * \text{dt} \tag{8.32}$$

Unit: Number of setup actions

The associated flow *performSetup_flow* is mainly driven by a predefined setup rate that is increased by the single process variety. Equation (8.33) shows the dependencies.

$$performSetup\_flow = setupRatePlan - setupRatePlan * 5.67 * ImpactFactor * Single\_Process\_Variety \tag{8.33}$$

Unit: Number of setup actions / Week

With the number of setup actions, the setup frequency over time can be calculated, which is an influencer to the workcenter standby time. Equation (8.34) shows the calculation.

$$setupFrequency = \frac{time()}{Nmbr\_SetupActions} \tag{8.34}$$

Unit: Timely Distance between setup action / week

The equipment lifespan is influenced by the percentage of reactive maintenance. The associations shown in Equation (8.35) are developed with dynamic variables. The simulation user must define a planned lifespan for the type of equipment from the analysed workcenter.

$$Equipment\_Lifespan = Equipment\_Lifespan\_Planned - Equipment\_Lifespan\_Planned * 8 * ImpactFactor * Percentage\_Of\_Reactive\_Maintenance \tag{8.35}$$

Unit: Years

Another element from the workcenter sub-model that is influenced by the percentage of reactive maintenance is the percentage of new equipment investment. The impact calculation follows Equation (8.36). In addition,in this case, the simulation user must define a planned percentage of new equipment investments that is increased by the percentage of reactive maintenance.

$$Percentage\_Of\_New\_Equipment\_Invests = Percentage\_Of\_New\_Equipment\_Invests\_Planned + Percentage\_Of\_New\_Equipment\_Invests\_Planned * 6 * ImpactFactor * Percentage\_Of\_Reactive\_Maintenance \tag{8.36}$$

Unit: Percentage / Year

8.5.3 Focus Operation Sub-Model

8.5.3.1 General Model Structure

The focus operation sub-model consolidates all variables that are related to associations within the selected focus operation. It also contains the PS-oriented KPIs on and operational level. The sub-model is mainly controlled through a processing rate that is applied to the current number of wafers that must be processed within the focus operation. Figure 8-6 shows the graphical sub-model structure.

The sub-model consists of following stock variables (gold-coloured in the sub-model) that interact with other model elements:

- InProcessWafers
- ToReworkWafers
- GoodWafers
- ScrapWafers

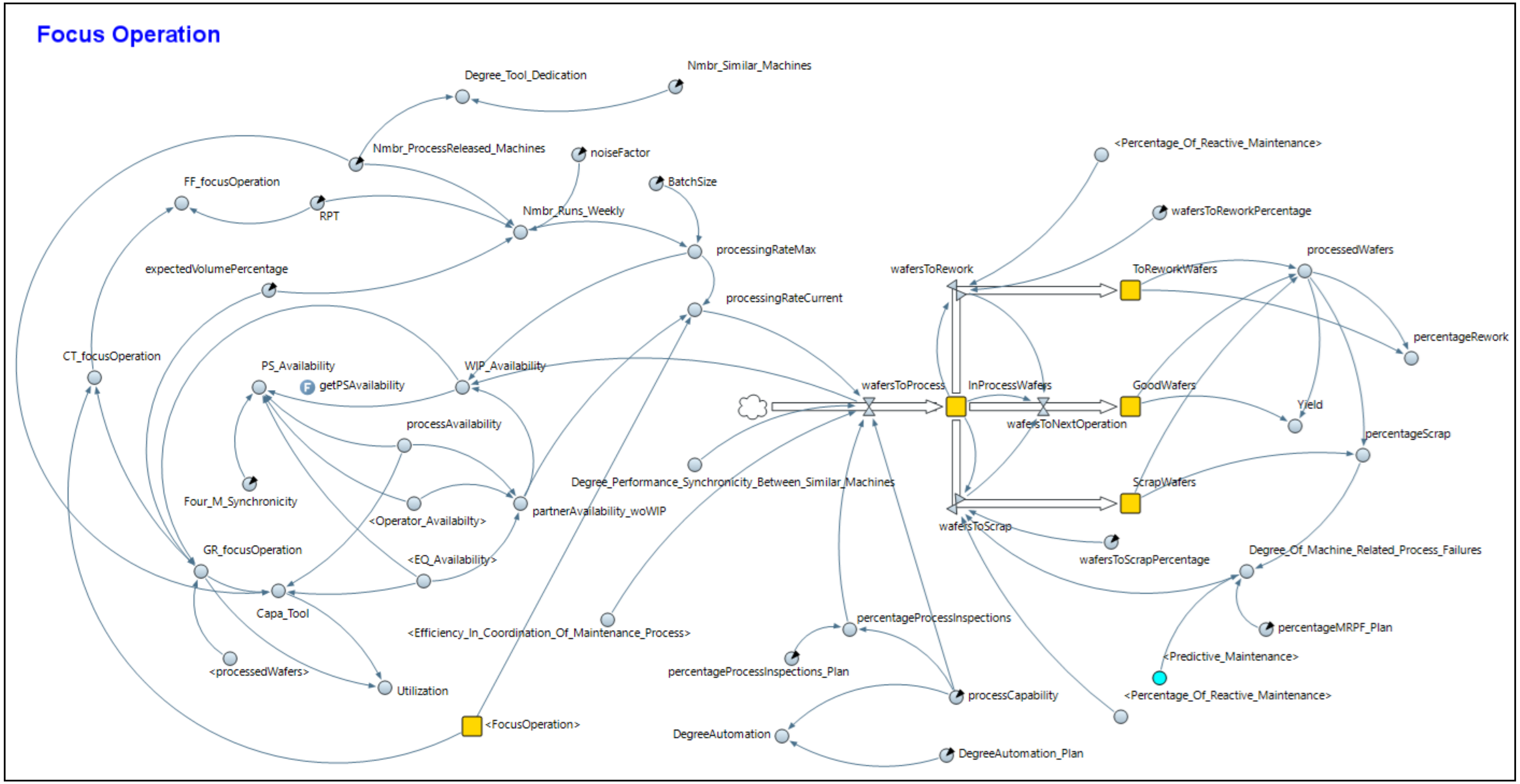


Figure 8-6: Focus Operation Sub-Model

8.5.3.2 Model Elements and Equations

The sub-model requires a set of parameters as input for the equations. Table 8-5 explains the meaning and units of these variables.

Table 8-5: Parameters for the Focus Operation Sub-Model

Parameter	Unit	Description
RPT	Week	Represents the raw process time for the selected focus operation.
Nmbr_ProcessReleased_Machines	Number of Machines	Represents the number of machines that are officially released to execute the focus operation.
Nmbr_Similar_Machines	Number of Machines	Represents the number of machines that are able to execute the focus operation principally.
Four_M_Synchronicity	Boolean	Indicates whether the four partners are synchronized for the focus operation or not.
Batch Size	Items / Machine	Represents the planned number of wafers that are processed in parallel during the focus operation using one machine.
expectedVolumePercentage	Percentage [0-1] /week	Represents the planned percentage of the focus operation for the workcenter compared to other operations that also use the workcenter.
wafersToReworkPercentage	Percentage [0-1]	Represents the average percentage of wafers that must perform a rework process due to quality issues at the focus operation.
wafersToScrapPercentage	Percentage [0-1]	Represents the average percentage of wafers that are damaged and must be removed from the production line due to quality issues at the focus operation.
processCapability	Index value	Represents the value from the process capability index for the focus operation.
DegreeAutomation_Plan	Percentage [0-1]	Represents the planned degree of automation at the focus operation. The value indicates the percentage of activities to execute operation that are planned to be automated compared to manual activities.
percentageProcessInspections_Plan	Percentage [0-1]	Represents the planned percentage of wafers that must pass process inspections.
percentageMRPF_Plan	Percentage [0-1]	Represents the expected percentage of scrapped wafers that were damaged due to machine-related process failures.
wasteFactor	Factor [0-1]	Represents the noise of the selected operation that cannot be influenced by any of the model elements. Examples for this are manual preparations or machine cleaning. The wasteFactor reduces the possible amount of runs per week.

The focus operation sub-model is driven by the process speed in which the current operation WIP can be processed. The wafers under process are stored in the stock variable *InProcessWafers* that is defined by Equation (8.37).

$$InProcessWafers = InProcessWafers_0 + \int_0^t (wafersToProcess - wafersToRework - wafersToScrap - wafersToNextOperation) * \mathrm{dt} \quad (8.37)$$

Unit: Items

The ingoing flow *wafersToProcess* adds wafers to the stock and is defined by Equation (8.38). This flow controls the speed of the focus operation that is evaluated with performance KPIs. The terms ‘Process Stability’ and ‘Process Maturity’ are merged into ‘Process Capability’, which is the more established term in manufacturing. ‘Process Capability’ expresses both aspects implicitly, and thus, it can be treated as the same source effect. The quantified causal relationships are transferred to the merged term. The values of duplicate associations are averaged.

$$wafersToProcess = limitMin(0, limitMax(FocusOperation, processingRateCurrent - 5 * ImpactFactor * Degree\_Performance\_Synchronicity\_Between\_Similar\_Machines * processingRateCurrent + 5 * ImpactFactor * Efficiency\_In\_Coordination\_Of\_Maintenance\_Process * processingRateCurrent - 3 * ImpactFactor * percentageProcessInspections * processingRateCurrent + 5.74 * ImpactFactor * processCapability * processingRateCurrent)) \quad (8.38)$$

Unit: Items / Week

The variable *processingRateCurrent* provides the number of wafers that can be processed within the configured operation environment; these are the available operation WIP, the maximum processing rate based on physical limits and the rate reduction due to partner availability. The maximum processing rate results from the weekly number of runs based on the operation RPT, the expected percentage of production volume for this particular operation and the average batch size that is used at the selected operation.

One of the outgoing flows is called *wafersToRework* and addresses the wafers that must be reworked. The flow is influenced by the percentage of reactive maintenance and is defined by Equation (8.39)

$$\begin{aligned} wafersToRework = {} & wafersToReworkPercentage * inProcessWafers \\ & + (wafersToReworkPercentage * inProcessWafers) * 10 \\ & * ImpactFactor * Percentage\_Of\_Reactive\_Maintenance \end{aligned} \tag{8.39}$$

Unit: Items / Week

Another outgoing flow that is called *wafersToScrap* moves items from the stock *InProcessWafers* to the stock *ScrapWafers*. This flow is also influenced by the percentage of reactive maintenance, in addition to the degree of machine-related process failures. Equation (8.40) shows the definition.

$$\begin{aligned} wafersToScrap = {} & wafersToScrapPercentage * inProcessWafers \\ & - (wafersToScrapPercentage * inProcessWafers) * 6 * ImpactFactor \\ & * Percentage\_Of\_Reactive\_Maintenance \\ & + (wafersToScrapPercentage * inProcessWafers) * 8.67 \\ & * ImpactFactor * Degree\_Of\_Machine\_Related\_Process\_Failures \end{aligned} \tag{8.40}$$

Unit: Items / Week

The third outgoing flow refers to the good wafers that are moved to the next operation of the product route. The difference between all wafers in the process and the wafers to rework and wafers to scrap is the value of this flow. Equation (8.41) shows the definition.

$$\begin{aligned} & wafersToNextOperation \\ & \quad = inProcessWafers - wafersToRework - wafersToScrap \end{aligned} \tag{8.41}$$

Unit: Items / Week

To compare the quantitative impact of PdM on the operation performance, the focus operation sub-model consists of the KPIs GR, CT, FF, $Capa_{Tool}$, Utilization and all types of availability. This collection allows a simulation user to compare the results at one glance. The calculation rules are partially modified compared to Chapter 4 to meet the simulation requirements. For instance, the number of process-released machines multiplies $Capa_{Tool}$, because the operation GR includes multiple machines. Otherwise, the Utilization value would indicate a wrong result.

8.5.4 Equipment Maintenance Sub-Model

8.5.4.1 General Model Structure

The EM sub-model consists of elements and characteristics that are crucial for maintenance activities within a SI PS. The core of the model is the percentages of reactive and preventive maintenance. These two values control all other variables. Another important element of the model is the variable that refers to the application of PdM. This variable calls a parameter 'PdM_Active' that can be configured at the simulation start. Because the partner company did not provide any data on the speed of reactions, or the probability to avoid late effects and other EM performance indicators, these aspects are covered by dynamic variables, and therefore, algebraic equations primarily. There is no advantage for the simulation quality if a stock and flow structure would be applied instead. It would increase the model complexity without the provision of deeper insights how PdM influences the PS performance in SI. However, a further study that is concentrated on EM performance in SI can collect and model these details based on this thesis. Figure 8-7 shows the sub-model structure visually.

The sub-model consists of following stock variables (gold-coloured in the sub-model) that are interacting with other model elements:

- Nmbr_EM_Reserve
- Nmbr_EM_OnShift
- Nmbr_EM_OOS

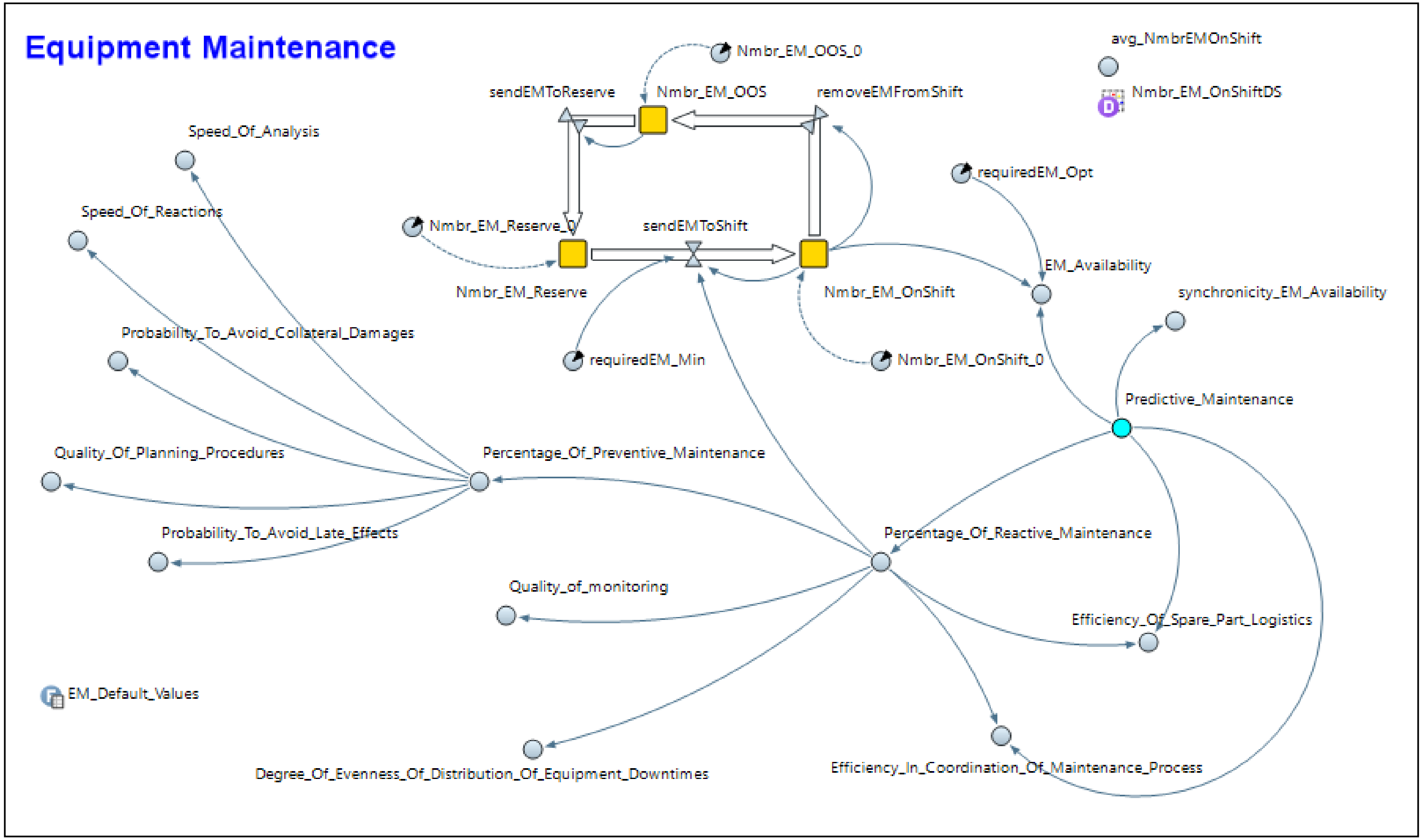


Figure 8-7: EM Sub-Model

8.5.4.2 Model Elements and Equations

The sub-model requires a set of parameters as input for the equations. Table 8-6 explains the meaning and unit of these variables.

Table 8-6: Parameters for the EM Sub-Model

Parameter	Unit	Description
requiredEM_Min	Number of Persons	Represents the minimum number of EM persons that are required to execute daily activities at the selected workcenter to keep the machines up and running. However, high risk of long downtimes remains in case of expensive and unplanned failures.
requiredEM_Opt	Number of Persons	Represents the optimum number of EM persons that are required to execute daily activities at the selected workcenter to keep the machines up and running. The Risk of long downtimes in case of expensive and unplanned failures is reduced due to sufficient EM capacity.
EM_Default_Values	Array of Percentages [0-1]	Represents an array of percentages from 0 to 1 that can be assigned as default values to the dynamic variables.
Nmbr_EM_OOS_0	Number of Persons	Represents the initial value for the stock variable *Nmbr_EM_OOS*.
Nmbr_EM_Reserve_0	Number of Persons	Represents the initial value for the stock variable *Nmbr_EM_Reserve*.
Nmbr_EM_OnShift_0	Number of Persons	Represents the initial value for the stock variable *Nmbr_EM_OnShift*.

The sub-model consists of three interacting stock variables that exchange a number of EM persons. The first stock variable is called *Nmbr_EM_Reserve* and stores the number of EM persons who are principally available at the company, who are qualified for the selected workcenter and who are not yet on shift. Equation (8.42) shows the definition.

$$Nmbr\_EM\_Reserve = Nmbr\_EM\_Reserve_0 + \int_0^t (sendEMToReserve - sendEMToShift) * \mathrm{d}t \tag{8.42}$$

Unit: Number of Persons

The second stock variable is called *Nmbr_EM_OnShift* and stores the number of EM persons that are currently on shift for the selected workcenter. The stock variable receives values from the *Nmbr_EM_Reserve* and sends values of the stock variable *Nmbr_EM_OOS.* Equation (8.43) shows the definition.

$$Nmbr\_EM\_OnShift = Nmbr\_EM\_OnShift_0 + \int_0^t (sendEMToShift - removeEMFromShift) * \mathrm{dt} \tag{8.43}$$

Unit: Number of Persons

The flow that connects both stock variables is called *sendEMToShift* and is defined by Equation (8.44). The minimum number of required EM persons on shift and the percentage of reactive maintenance drive influence the flow. To be more specific, a growing percentage of reactive maintenance increases the required minimum number.

$$sendEMToShift = Nmbr\_EM\_OnShift < requiredEM\_Min + requiredEM\_Min * 6.5 * ImpactFactor * Percentage\_Of\_Reactive\_Maintenance \,?\, Nmbr\_EM\_Reserve : 0 \tag{8.44}$$

Unit: Number of Persons / Week

The stock variable *Nmbr_EM_OOS* stores the number of EM persons that are currently out of service, and therefore, unavailable for shift. Equation (8.45) shows the formula.

$$Nmbr\_EM\_OOS = Nmbr\_EM\_OOS_0 + \int_0^t (removeEMFromShift - sendEMToReserve -) * \mathrm{dt} \tag{8.45}$$

Unit: Number of Persons

The outgoing flow *removeEMFromShift* assumes that EM persons have rest times and are not available every day within a year. Every week, the flow removes an estimated percentage (20%) of EM persons from the shift. To keep the EM persons on shift for at least one week, the flow applies a delay function. Equation (8.46) presents these logics.

$$removeEMFromShift = delay(limitMin(0, Nmbr\_EM\_OnShift * 0.2), 1, 0) \tag{8.46}$$

Unit: Number of Persons / Week

Once the EM persons have completed their recovery, they are sent to the pool of staff that can be appointed to support any shift during the week. The simulation model also assumes in this case one week of recovery, therefore, a delay function is applied. The resulting flow is called *sendEMToReserve* and defined by Equation (8.47).

$$sendEMToReserve = delay(limitMin(0, Nmbr\_EM\_OOS), 1, 0) \tag{8.47}$$

Unit: Number of Persons / Week

The stock variable *Nmbr_EM_OnShift* is one of the required elements to calculate the EM availability. To compare the number of EM persons on shift over the simulation horizon with and without PdM application, the weekly stock values are stored in a dataset. The variable *avg_NmbrEMOnShift* returns the mean value of these data points. This value can be compared for both simulation scenarios.

8.5.5 Operator Sub-Model

8.5.5.1 General Model Structure

The operator sub-model consists of elements that are related to the operators who operate machines and perform manual actions as far as required by the focus operation. The direct influences of PdM are limited to the motivation of operators, which then influences the operator availability. Another influencing factor is the degree of automation at the selected workcenter that affects the degree of operator qualification level. This level has also influence on the operator availability. Figure 8-8 shows the visual structure of the sub-model.

The sub-model consists of following stock variables (gold-coloured in the sub-model) that interact with other model elements:

- UnmotivatedOperators
- MotivatedOperators

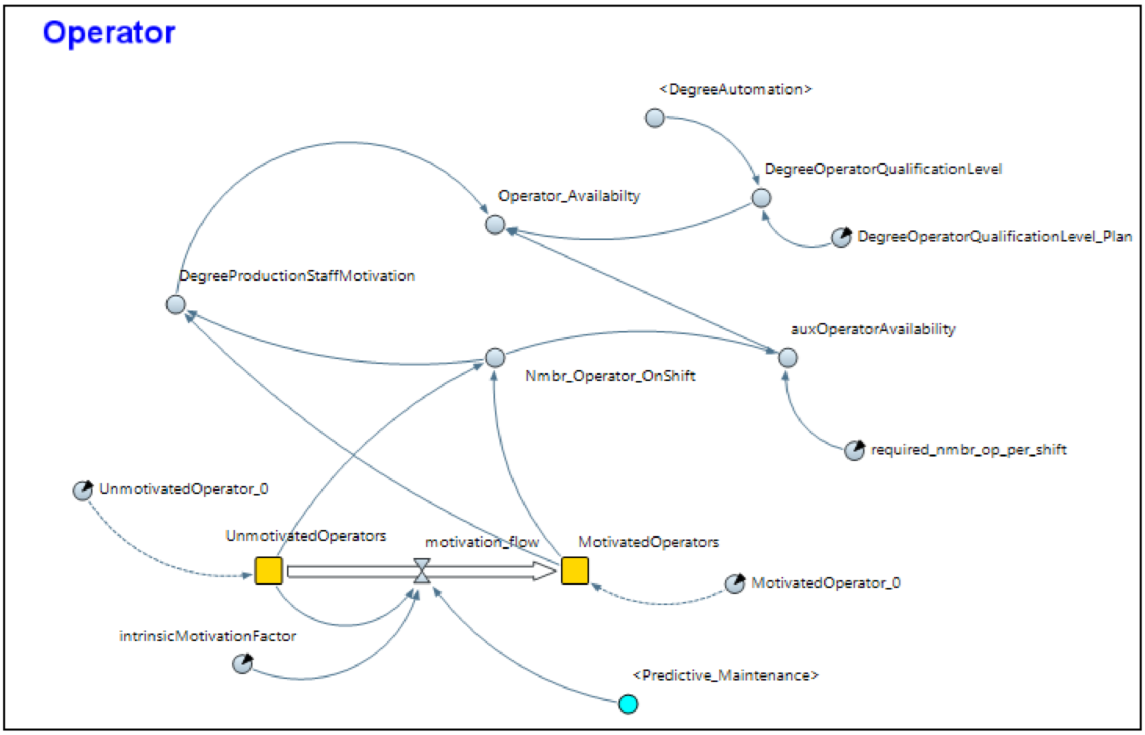


Figure 8-8: Operator Sub-Model

8.5.5.2 Model Elements and Equations

The sub-model requires a set of parameters as input for the equations. Table 8-7 explains the meaning and unit of these variables.

The sub-model consists of two stock variables that represent operators that are either motivated or unmotivated. The stock variable *UnmotivatedOperators* is defined by Equation (8.48) and is reduced by a motivation flow.

$$UnmotivatedOperators = UnmotivatedOperators_0 - \int_0^t (motivation\_flow) * \mathrm{dt} \quad (8.48)$$

Unit: Number of Persons

The receiving stock is called MotivatedOperators and is defined by Equation (8.49).

$$MotivatedOperators = MotivatedOperators_0 + \int_0^t (motivation\_flow) * \mathrm{dt} \quad (8.49)$$

Unit: Number of Persons

Table 8-7: Parameters for the Operator Sub-Model

Parameter	Unit	Description
intrinsicMotivationFactor	Percentage [0-1]	Represents an intrinsic factor that increases motivation of the operator staff without external influences.
required_nmbr_op_per_shift	Number of Persons	Represents the optimum number of operators that are required to execute the focus operation at the selected workcenter to keep the machines up and running. The risk of long standby times is reduced due to sufficient operator capacity.
DegreeOperatorQualificationLevel_Plan	Percentage [0-1]	Represents the planned degree of operator qualification that is required for the focus operation.
UnmotivatedOperator_0	Number of Persons	Represents the initial value for the stock variable *UnmotivatedOperators*.
MotivatedOperator_0	Number of Persons	Represents the initial value for the stock variable *MotivatedOperators*.

Both stock variables are directly connected through a flow that is called *motivation_flow* and defined by Equation (8.50).

$$\begin{aligned} motivation\_flow = {} & UnmotivatedOperators * ImpactFactor \\ & * intrinsicMotivationFactor + UnmotivatedOperators * 6 \\ & * ImpactFactor * Predictive\_Maintenance \end{aligned} \tag{8.50}$$

Unit: Number of Persons / Week

The degree of production staff motivation is calculated based on the relation between these two stock variables. It influences the operator availability in addition to the degree of operator qualification.

8.5.6 Costs Sub-Model

8.5.6.1 General Model Structure

The costs sub-model contains elements that represent the different aspects of costs within the SI PS that a PdM application would influence. The different types of costs are modelled as stock variables that are driven by a fixed cost rate. Each cost rate is influenced by one or more variables from other sub-models. Based on the collected interview data, the details on cost-specific associations are limited. Therefore, the sub-model does not consist of further intelligence beyond the impacts of these variables from the other sub-models. To compare the cost effects of PdM, it is not important to set an initial value for the stock variables. Thus, the initial value is zero for all costs. The analysis is performed by comparing the final values of the stock variables with and without applying PdM.

The sub-model consists of following stock variables (gold-coloured in the sub-model) that are interacting with other model elements:

- Personnel_Costs
- EM_Costs
- Inventory_Costs
- Spare_Part_Costs
- Product_Costs

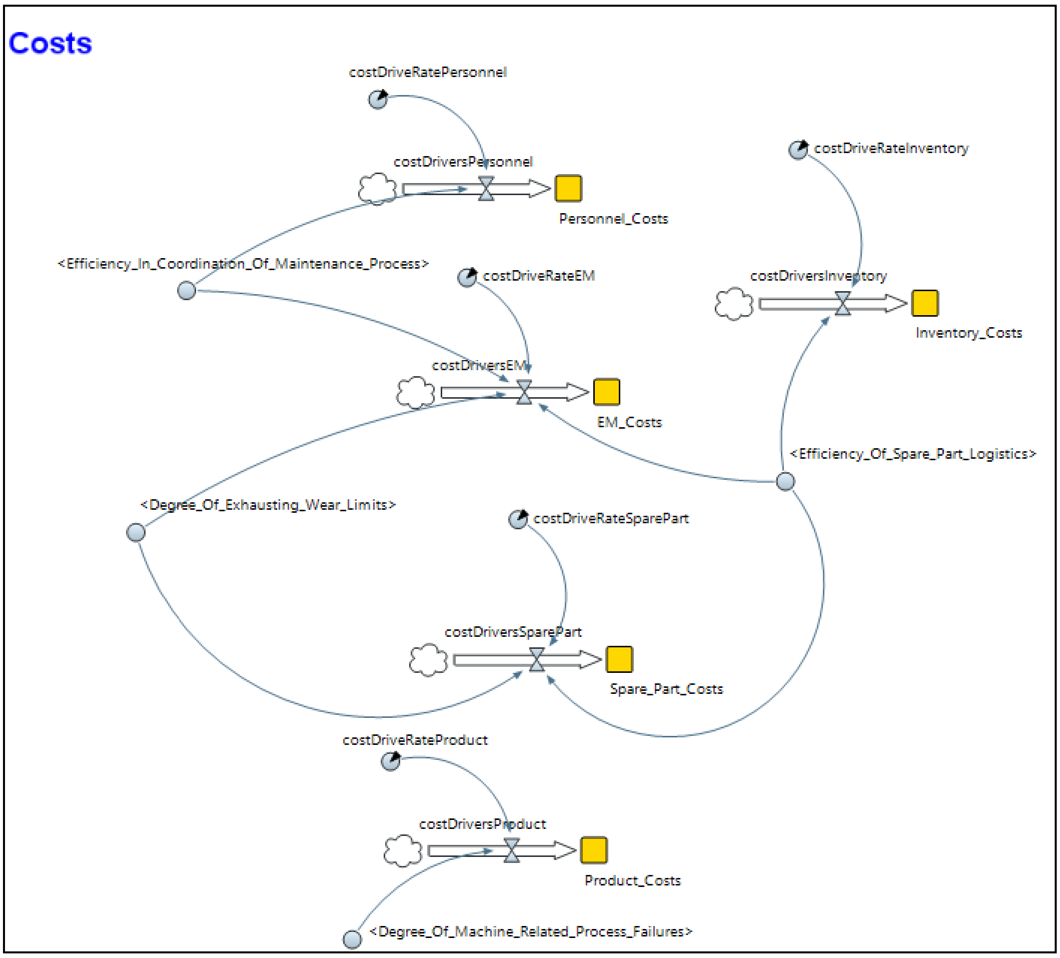


Figure 8-9: Costs Sub-Model

8.5.6.2 Model Elements and Equations

The sub-model requires a set of parameters as input for the equations. Table 8-8 explains the meaning and unit of these variables.

Table 8-8: Parameters for the Costs Sub-Model

Parameter	Unit	Description
costDriveRatePersonnel	Monetary Unit / Week	Represents the weekly costs for production personnel.
costDriveRateSparePart	Monetary Unit / Week	Represents the weekly costs for spare parts.
costDriveRateEM	Monetary Unit / Week	Represents the weekly costs for EM beyond personnel.
costDriveRateInventory	Monetary Unit / Week	Represents the weekly costs for inventory beyond spare parts.
costDriveRateProduct	Monetary Unit / Week	Represents the weekly costs for product beyond all other mentioned above.

The sub-model stock variables are not directly associated and do not mutually pass or receive costs. The stock variable *Personnel_Costs* grows by a cost drivers flow and is defined by Equation (8.51).

$$Personnel\_Costs = Personnel\_Costs_{\,0} + \int_0^t (costDriversPersonnel) * \mathrm{dt} \tag{8.51}$$

Unit: Monetary Unit

The associated flow is influenced by the efficiency in coordination of maintenance process and defined by Equation (8.52).

$$\begin{aligned} costDriversPersonnel \\ &= costDriveRatePersonnel - costDriveRatePersonnel * 8 \\ &* ImpactFactor \\ &* Efficiency\_In\_Coordination\_Of\_Maintenance\_Process \end{aligned} \tag{8.52}$$

Unit: Monetary Unit / Week

The EM costs are stored in the stock variable *EM_Costs* that is defined by Equation (8.53).

$$EM\_Costs = EM\_Costs_{\,0} + \int_0^t (costDriversEM) * \mathrm{dt} \tag{8.53}$$

Unit: Monetary Unit

The according flow *costDriversEM* is influenced by efficiency improvements and the degree of exhausting wear limits and is defined by Equation (8.54).

$$\begin{aligned} costDriversEM = costDriveRateEM - costDriveRateEM * 7 * ImpactFactor \\ &* Degree\_Of\_Exhausting\_Wear\_Limits - costDriveRateEM * 5.5 \\ &* ImpactFactor \\ &* Efficiency\_In\_Coordination\_Of\_Maintenance\_Process \\ &- costDriveRateEM * 6 * ImpactFactor \\ &* Efficiency\_Of\_Spare\_Part\_Logistics \end{aligned} \tag{8.54}$$

Unit: Monetary Unit / Week

The spare part costs are stored in the stock variable *Spare_Part_Costs* that is defined by Equation (8.55).

$$Spare\_Part\_Costs = Spare\_Part\_Costs_{\,0} + \int_0^t (costDriversSparePart) * \mathrm{dt} \tag{8.55}$$

Unit: Monetary Unit

The following flow *costDriversSparePart* is defined by Equation (8.56).

$$costDriversSparePart = costDriveRateSparePart - costDriveRateSparePart * 7.5 * ImpactFactor * Degree\_Of\_Exhausting\_Wear\_Limits - costDriveRateSparePart * 5 * ImpactFactor * Efficiency\_Of\_Spare\_Part\_Logistics \quad (8.56)$$

Unit: Monetary Unit / Week

Any other inventory costs beyond the actual spare part costs are stored in the stock variable *Inventory_Costs* that is defined by Equation (8.57).

$$Inventory\_Costs = Inventory\_Costs_{\,0} + \int_0^t (costDriversInventory) * \mathrm{dt} \quad (8.57)$$

Unit: Monetary Unit

The according flow *costDriversInventory* is defined by Equation (8.58).

$$costDriversInventory = costDriveRateInventory - costDriveRateInventory * 4 * ImpactFactor * Efficiency\_Of\_Spare\_Part\_Logistics \quad (8.58)$$

Unit: Monetary Unit / Week

The stock variable *Product_Costs* stores all other types of costs that are required to manufacture the selected product. It is defined by Equation (8.59).

$$Product\_Costs = Product\_Costs_{\,0} + \int_0^t (costDriversProduct) * \mathrm{dt} \quad (8.59)$$

Unit: Monetary Unit

The associated flow *costDriversProduct* is defined by Equation (8.60).

$$costDriversProduct = costDriveRateProduct + costDriveRateProduct * 10 * ImpactFactor * Degree\_Of\_Machine\_Related\_Process\_Failures \quad (8.60)$$

Unit: Monetary Unit / Week

8.5.7 Creation of User Interface for Simulation

To execute the simulation model and to configure the parameters for a particular scenario, a user interface is developed to support the model end-users. There is one parameter box for each sub-model and for general model setting. The main benefits for a model user are that the simulation runs need not to be cancelled and restarted to change parameter values and that the modification of values is much more convenient than in the AnyLogic editor. Figure 8-10 shows a part of the simulation frame where a user can configure the general settings and the workcenter-specific parameters. It represents the user interface at the runtime.

As visualized in the figure, default values are configured for each parameter. This initial value set supports the model user to understand the value dimensions and ranges. In addition, the user can perform a demonstration run without any personal configuration just to understand the model logics and dynamics. The ‘General Model Specification’ section consists of two important parameters that affect all sub-models. If the checkbox ‘Predictive Maintenance Active’ is checked, the quantitative impacts that are caused by PdM are considered in the current simulation scenario. A model user must configure all sub-models by selection of the particular parameters and can execute the simulation at first without and then with consideration of PdM impacts. Both simulation results must be compared based on the selected indictors such as the number of failures, processed wafers or sum of EM costs.

The other setting is called ‘Impact Factor’. This controls the weight of all impact associations including the PdM associations. A number of experiments have been carried out to refine the impact factor. The results of these experiments lead to a useful range from 0 to 0.03. Impact factor values beyond 0.03 lead to extraordinary effects that do not produce valid results. A differentiation between online and offline PdM has not been simulated since the association target terms do not have any impact on production performance. Therefore, the level of quantitative insight would not increase. Nevertheless, the PPES considers this differentiation in a logical way as discussed in Chapter 5.

Where applicable, the input controls have minimum and maximum values stored. This prevents users from configuring the simulation model wrongly. This type of limitation is configured for all variables that depict a percentage or probability. Figure 8-11 demonstrates how a value range between zero and one is configured for the percentage of spare part replacements.

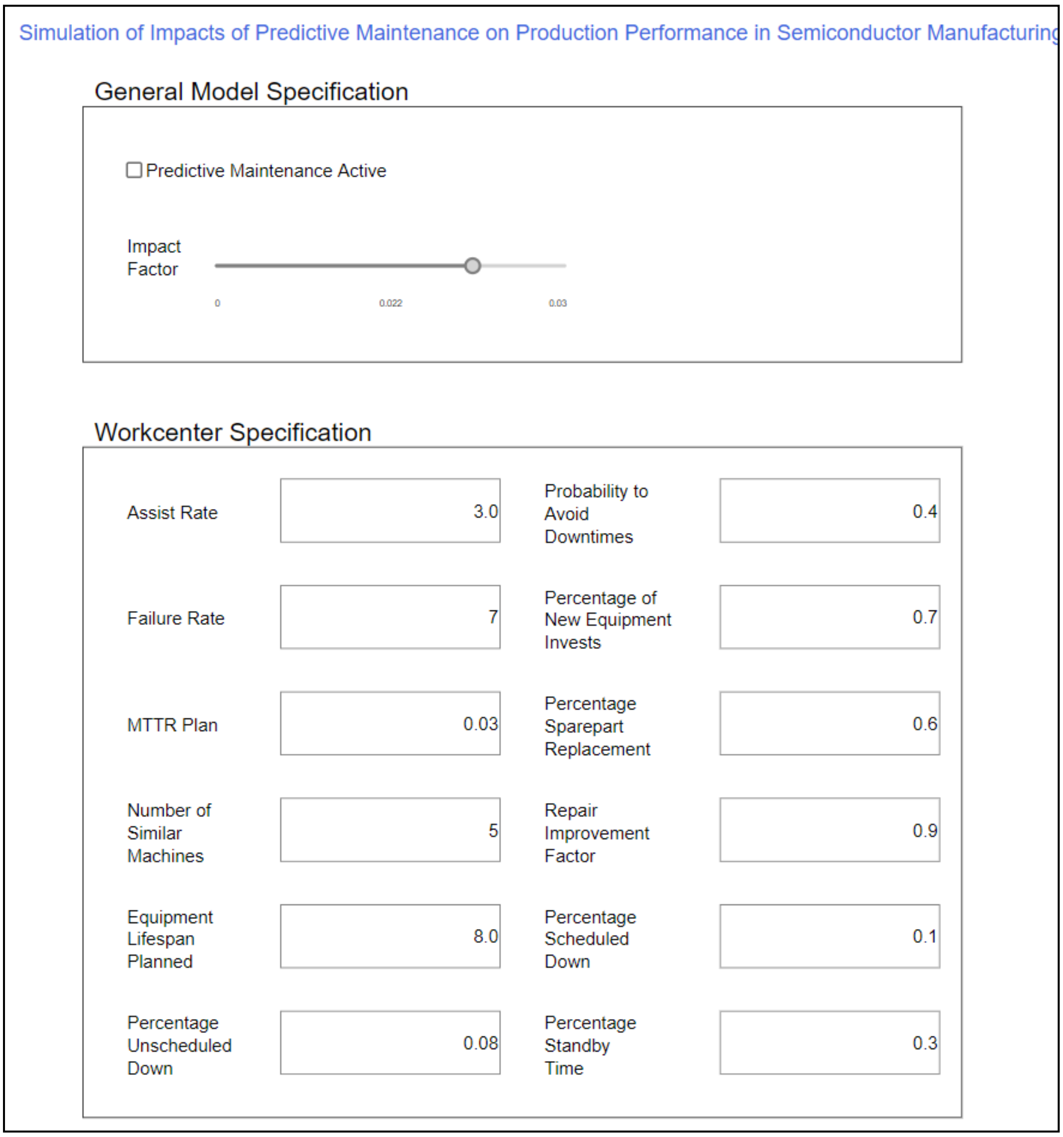


Figure 8-10: Part of the Simulation User Interface to Configure General and Workcenter-specific Parameters

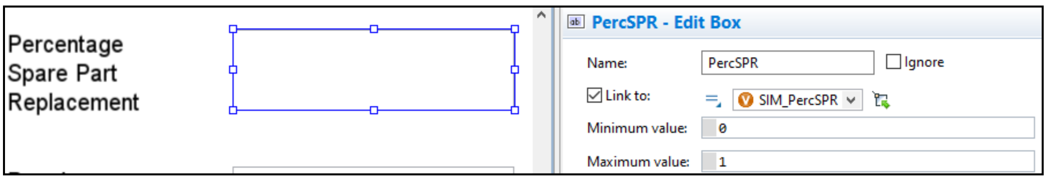


Figure 8-11: Configuration of Allowed Value Ranges

Further limitations must be considered for parameters that are logically dependent. This consideration affects the percentages of equipment times as well as the percentages of wafer to scrap and wafer to rework. Each set of parameters in the sum is not allowed to exceed the number one. Figure 8-12 shows the proper configuration for the percentage of wafers to rework that considers the percentage of wafers to scrap in the maximum value formula.

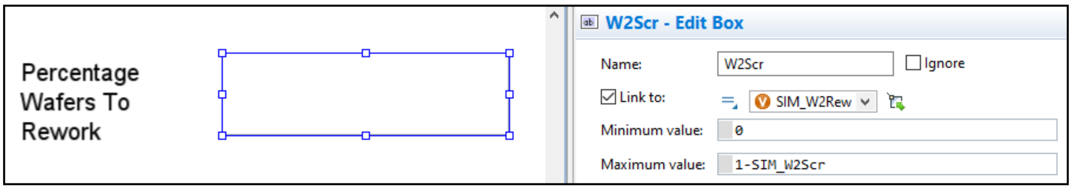


Figure 8-12: Configuration of Allowed Value Ranges with Dependency to other Parameters

Input controls can be from different types, such as textbox, checkbox or slider. The most appropriate control must be selected for each parameter. Boolean parameters are configured as checkboxes and few parameters can be changed through sliders because a concrete value does not exist in reality. The majority of parameters is configured as textboxes that allow the entering of concrete values from company databases. After deselecting an input control or when clicking the simulation start button, AnyLogic simulation engine validates the user input and readjusts the values based on the given ranges.

Although the simulation frame and the main agent type, which contains the sub-models, are part of the same AnyLogic model file, they are not fully connected. This leads to the restriction that an input control from the simulation frame cannot directly write to a model parameter. For this purpose, AnyLogic requires specific simulation variables as transfer elements. Each parameter and input control is connected through a simulation variable and all of these participants are created and configured independently. Figure 8-13 shows the basic configuration of a simulation variable.

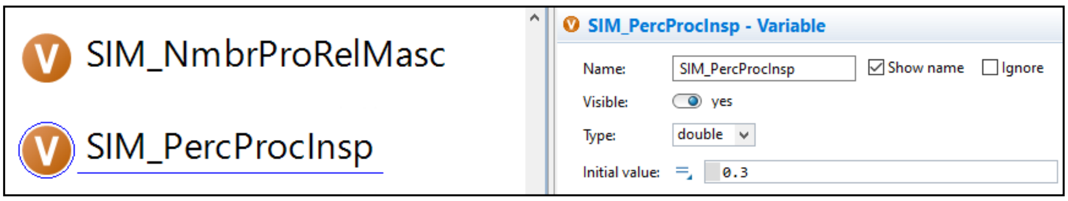


Figure 8-13: Configuration of Simulation Variables

A variable must have a data type that meets the requirements of the related parameter. The example from the figure uses ‘double’ because it refers to a percentage in decimal format. An initial value for an input control comes from this variable definition.

Figure 8-14 shows the entire data binding process that must be configured for each parameter. The parameter default value from the lowest part of the figure is required if this described data binding is not configured. Once the data binding is configured properly, the default value is overwritten by the passed value from the input control.

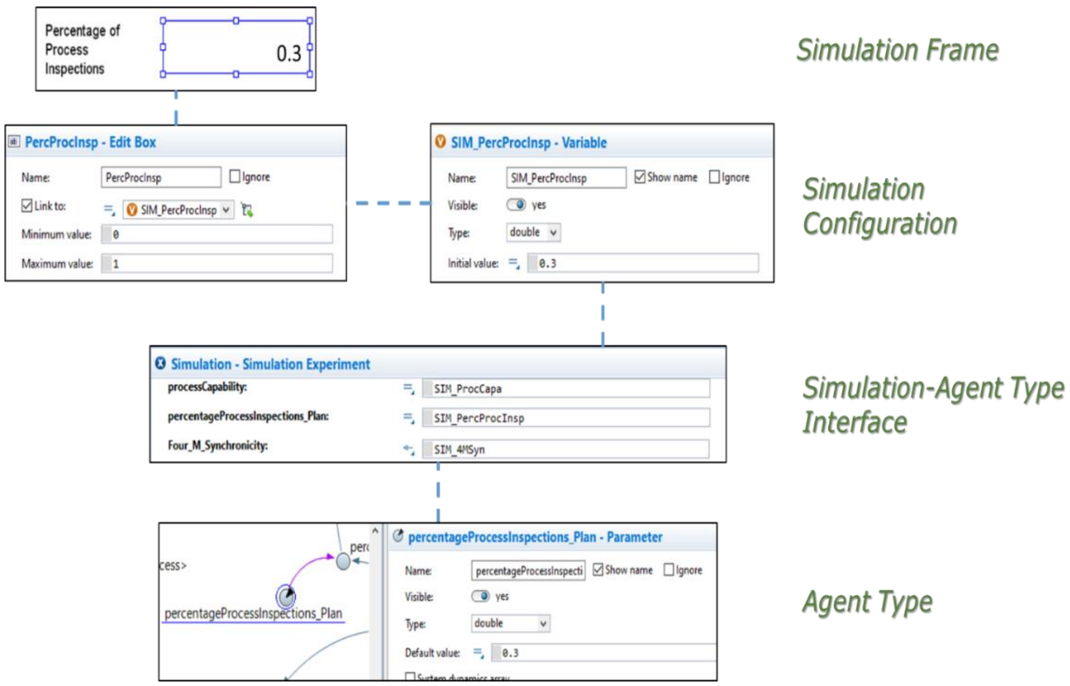


Figure 8-14: Data Binding from User Input to Sub-Model Parameter

8.6 Model Verification

Bossel (2004) pointed out that the overall correctness of a model cannot be proved in general. Even if the target application of this study generates reasonable results, it does not prove that other use cases beyond the scope of this thesis would generate correct results as well. However, the opposite can be proven: By testing if model results are unrealistic (e.g., they differ from the real system) or illogical (e.g., the generated values are physically impossible), it can be stated that the model is inaccurate or wrong. Therefore, not the overall correctness but the validity of the developed model for the specific purpose shall be evaluated. According to Bossel (2004), the key aspects of validity are structure, behaviour, empiricism and application. Sterman (2000) described a set of test procedures against structural, empirical and behavioural validity. These ensure, for instance, that the relevant elements from the real system are considered in the model and that the model is robust against exhausting the specification limits or parameters (Sterman, 2000). Some of the validity aspects have already been discussed in Section 8.3 and are specifically considered during the model development. Therefore, it is not necessary to prove them again. In this thesis, a special validation method has been proposed for this particular model to test the crucial aspects based on Sterman's and Bossel's proposals. Table 8-9 lists the procedures, goals and test case specifications that are part of the validation method. The concrete test cases are discussed in the following sub-sections.

Table 8-9: Verification Method for PdMSM

Test Procedure	Goal	Test Case Specification	Pass Condition
Structure Assessment	Verify that modelled and real system structure are consistent.	Demonstrate that stock variables that refer to positive elements in reality cannot have negative values.	Model results for selected variables and a particular scenario are consistent.
Parameter Assessment	Verify that parameter values can be determined quantitatively.	Justify the parameter value retrieval.	It is comprehensibly explained how to determine initial values for selected parameters in real world.
Extreme Condition	Verify that the model is robust against exhausting the specification limits or parameters	Demonstrate that the model results are still consistent for extreme parameter values.	Model does not produce inconsistent values when exhausting the specification limits of selected parameters.
Empirical Validity	Verify that the trend of simulated values is consistent to the real system.	Compare core variables over one year between historical data and simulation results.	The dimension and trend of selected simulated values are consistent to the real system over a specific period.
Application Validity	Verify that the model supports the practical application purpose.	Demonstrate the comparison of two operations regarding the effects of PdM application.	The model can be applied as designed to discover and compare quantitative scenario-specific effects.

8.6.1 Structure Assessment

To verify the structural validity, the following test cases have been selected that follow the test case specification. All test cases use the same set of initial parameter values. The tests cases consider the experiments with and without the application of PdM.

1) Number of Failures is not negative.

Figure 8-15 shows the evolution of the stock variable '*Number_Failures*' with and without application of PdM over one year (in weeks). Since the simulated values are strongly related to the company performance, they are not allowed to be published. This stock variable is part of the workcenter sub-model and counts failures of a particular workcenter; it cannot be negative in reality.

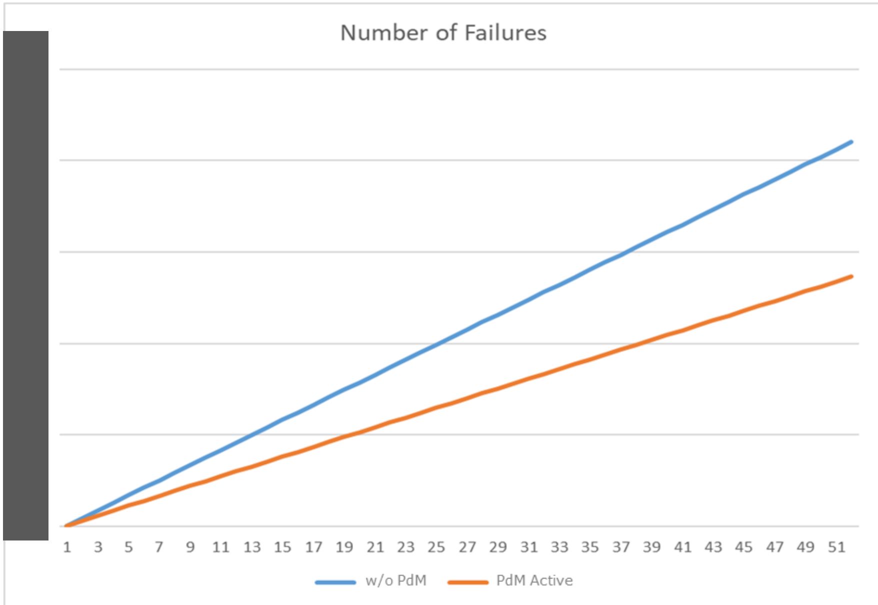


Figure 8-15: Structural Validity of Number of Failures

The blue line refers to normal execution of the model without application of PdM, whereas the orange line refers to the scenario that applies PdM. The results show that the number of failures cannot become negative, neither without nor with application of PdM.

2) Unscheduled Downtime is not negative.

Figure 8-16 shows the evolution of the stock variable '*UnscheduledDownTime'* with and without application of PdM over one year (in weeks). Since the simulated values are strongly related to the company performance, they are not allowed to be published. This stock variable is also part of the workcenter sub-model and sums unscheduled downtimes of a particular workcenter; it cannot be negative in reality.

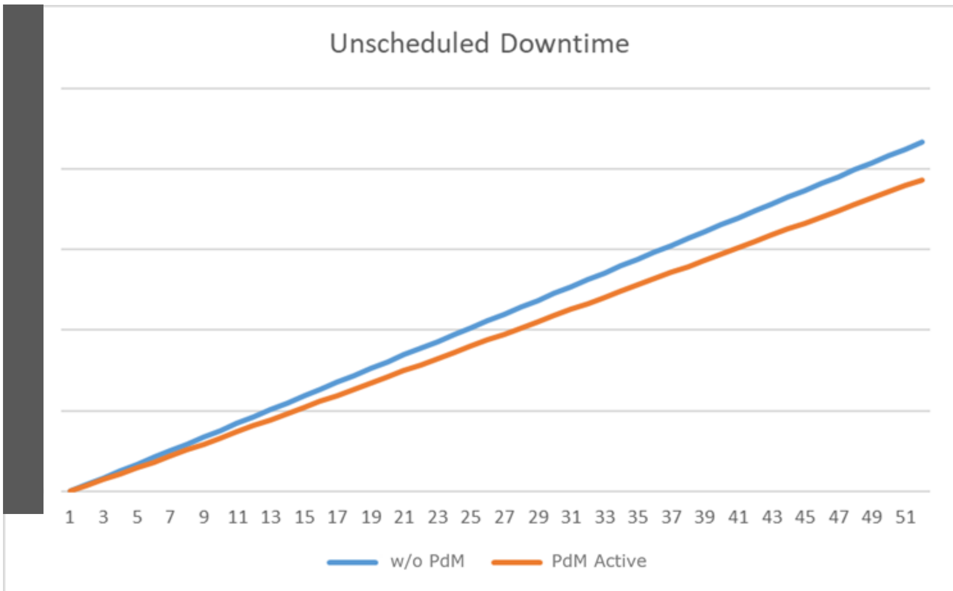


Figure 8-16: Structural Validity of Unscheduled Downtime

The blue line refers to normal execution of the model without application of PdM, whereas the orange line refers to the scenario that applies PdM. The results show that the unscheduled downtime cannot become negative, neither without nor with application of PdM.

3) WIP at Focus Operation is not negative.

Figure 8-17 shows the evolution of the stock variable '*FocusOperation*' with and without application of PdM over one year (in weeks). Since the simulated values are strongly related to the company performance, they are not allowed to be published. This stock variable is part of the production line sub-model and counts wafers that are waiting to be processed; it cannot be negative in reality. The blue line refers to normal execution of the model without application of PdM, whereas the orange line refers to the scenario that applies PdM.

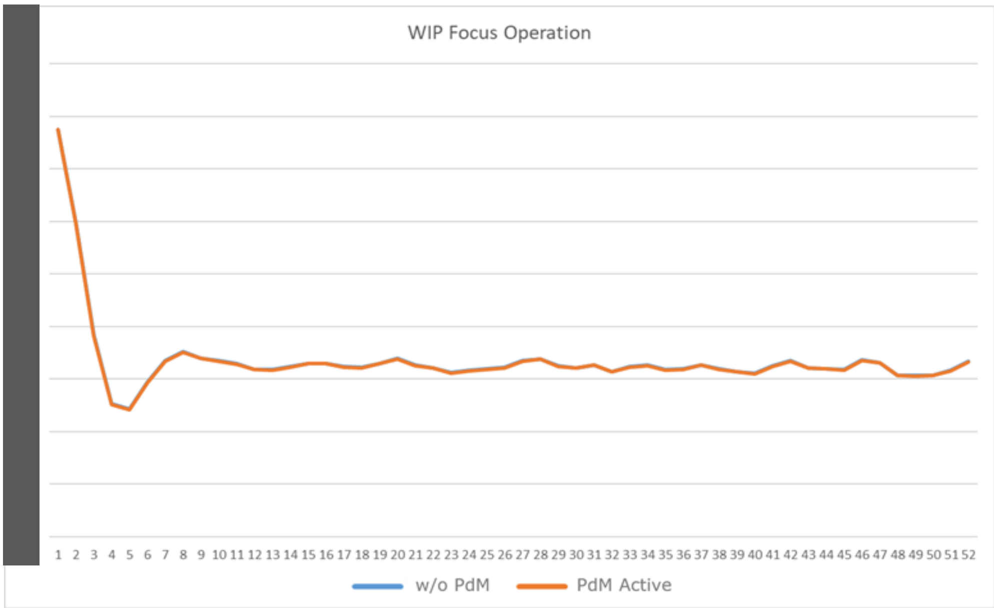


Figure 8-17: Structural Validity of WIP at Focus Operation

The results show that the WIP cannot become negative, neither without nor with application of PdM. In this scenario, there is no impact of PdM on WIP at focus operation at all, hence, the two lines are completely overlapping (the blue line is hidden).

8.6.2 Parameter Assessment

The parameters can be divided into quantifiable information and soft information. All types of quantifiable data that are required to initialise the model can be extracted from the databases that were discussed in Section 5.5. These are standard systems in SI PS. Therefore, the risk that other companies cannot collect the required information to configure the parameters is very low. The following cases were selected for the testing to investigate how to initialise the model for quantifiable parameters.

1) **Number of Similar Machines**

The case-study company uses a MDM system to manage machine-related information. Each machine record has an association to a workcenter record. This association indicates the similarity from a process perspective. The number of similar machines is the number of machine records, which point to the same workcenter record.

2) **Pre-Process Cycle Time**

The company's BI system consists of a module called 'CT & FF', which analyses the performance of single operations, or entire product routes within a specified timeframe in the past. The operation-specific performance data from the selected product route for the previous 12 months can be exported into an Excel file. After selecting the focus operation, the analyst knows the position of the operation within the product route, for instance, it could be on the 90th position out of a total of 140 operations. The analyst must calculate the CT mean of all operations over the previous 12 months. Then, the percentage of all operations up to the position of the focus operation, which is 64%, is multiplied by the CT mean value. This value is used for the parameter. It is important to apply the same logic to set the Pre-Process WIP value to ensure consistency when comparing different operations from the route.

3) **Required EM Technicians per Shift (Minimum)**

The ERP consists of a plant maintenance module to manage the maintenance activities. Based on the historical maintenance records and the plant shift schedule, the number of EM technicians that is required per shift to execute the stored maintenance activities can be extracted. The maintenance activities must be categorised into 'production-critical' and 'postponing-optional'. When only production-critical activities are considered, the required number of persons is used for the minimal parameter.

There is also soft information required to initialise the simulation model. This type of data is usually not extractable from databases but depends on expert assessment. For instance, the degree of operator qualification level must be expressed as a percentage from zero to one. Although the case study company uses a software-based qualification matrix to grant certificates to operators, a quantitative degree cannot be derived from the data because the specification limits are indeterminable. Therefore, a production leader with knowledge of the qualifications of his operator team must specify the degree based on his personal experience and opinion. A simulation user must apply this procedure for all parameters that require soft information.

8.6.3 Extreme Conditions

The goal of this test is to demonstrate that the model is robust against extreme parameter values. However, extreme values shall still consider realistic scenarios. For instance, a RPT that equals zero is not useful for demonstration purposes because it does not exist in the real PS. The following test cases demonstrate the robustness. The rest of the model configuration is equal to the other tests if not explicitly mentioned.

1) **Verify the model behaviour for an operation with a very small RPT value and with a very big RPT value.**

The first experiment uses a RPT that equals 0.05 hours, which means 3 minutes. For the second experiment, the RPT is set to 24 hours. To exclude other effects from overcapacity or low WIP availability, the number of process-released machines is set to one. Figure 8-18 shows the results of both experiments.

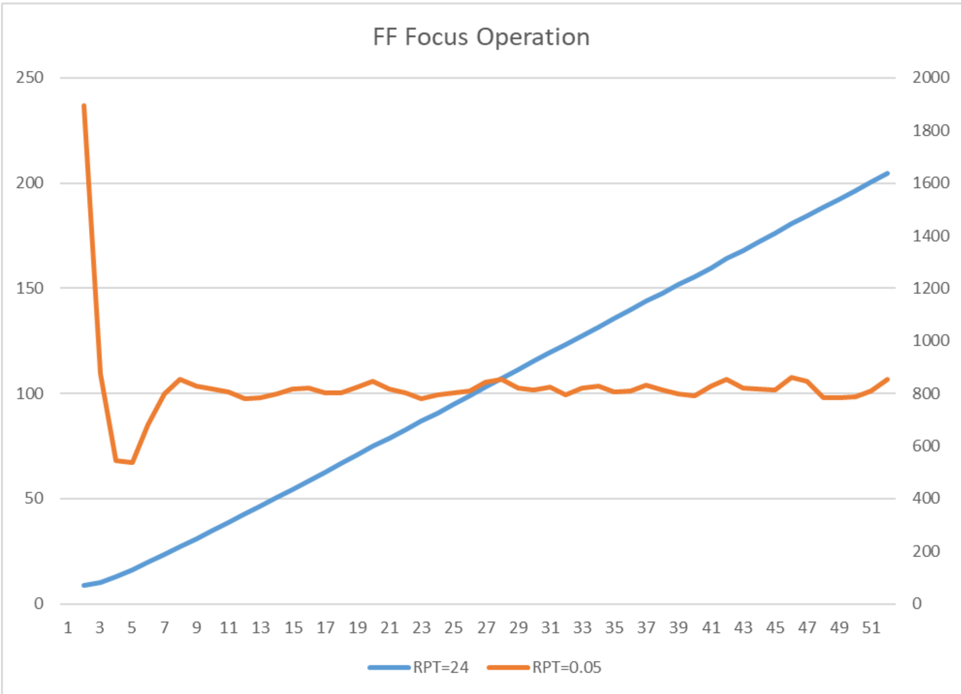


Figure 8-18: Comparison of FF at Focus Operation for Extreme RPT Values

The figure uses two vertical axes with different dimensions. The left axis belongs to the blue line (RPT=24), whereas the right axis belongs to the orange line (RPT=0.05). The courses of both lines are different and do not break out into unexpected directions. Both small and high RPTs lead to extremely high FF values but with different growth measures. Although the high RPT generates a lower FF at the beginning of the experiment, the FF grows over time due to the backlog of wafers in the focus operation WIP that cannot be processed due to the long process duration and limited capacity of only one machine. The small RPT generates an extremely high FF already at the beginning of the experiment. Although the FF decreases significantly after a few weeks, it remains at an extremely high level over the entire simulation period. This effect comes mainly from overcapacity and relatively low WIP at the focus operation. Despite the short RPT, the operation is dependent on the ingoing flow from the pre-process stock variable. The operation processes the same number of items within a week as it would process with a higher RPT due to these physical restrictions. Only the FF expresses a poor performance due to the low RPT.

2) **Verify the equipment availability with high and low unscheduled downtimes**.

The optimum for a workcenter performance would be the complete avoidance of unscheduled downtime, for instance, based on intelligent prediction algorithms. The first experiment sets UD to zero. The second experiment uses an extraordinary high percentage of unscheduled downtime. The input box is limited to 0.25 as the maximum value because of consideration of other causal effects that increase the initial percentage. From a practical perspective, such an average percentage of unplanned downtime over all machines within a workcenter is an indicator for an extremely poor performance. Figure 8-19 shows the results of both experiments.

An unscheduled downtime percentage of zero leads to an increased equipment availability. Because of existing standby time and scheduled downtime, the availability still does not reach 100%. In the second experiment, the level of equipment availability decreases by the difference of approximately 0.25. Both experiments generate reasonable values for equipment availability. These results demonstrate the model is robust against extreme UD values.

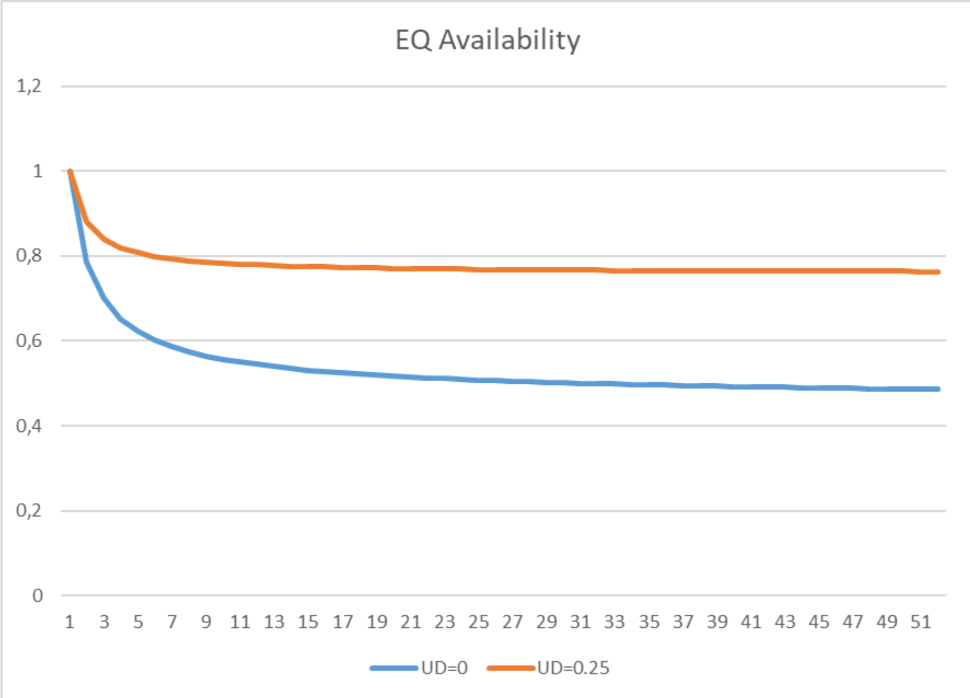


Figure 8-19: Comparison of Equipment Availability for Extreme UD Values

Further experiments have been performed to verify the robustness by applying extreme values for the percentage or reactive maintenance, the repair time, the cost rates and more. All of these experiments generated convincing results. This leads to the finding that the model is robust against extreme values, because the model does not produce inconsistent values when exhausting the specification limits of selected parameters.

8.6.4 Empirical Validity

To prove the empirical validity, the following test cases were executed to compare the results over one year between historical data from the case study company and simulation results.

1) **Compare dimension and development of WIP at focus operation**. Figure 8-20 shows the visual comparison of simulated and empirical values. The blue line refers to the simulated results without application of PdM, whereas the grey line represents the empirical data for WIP at the selected operation. The actual values are not allowed to be published since they depict confidential information about the company performance.

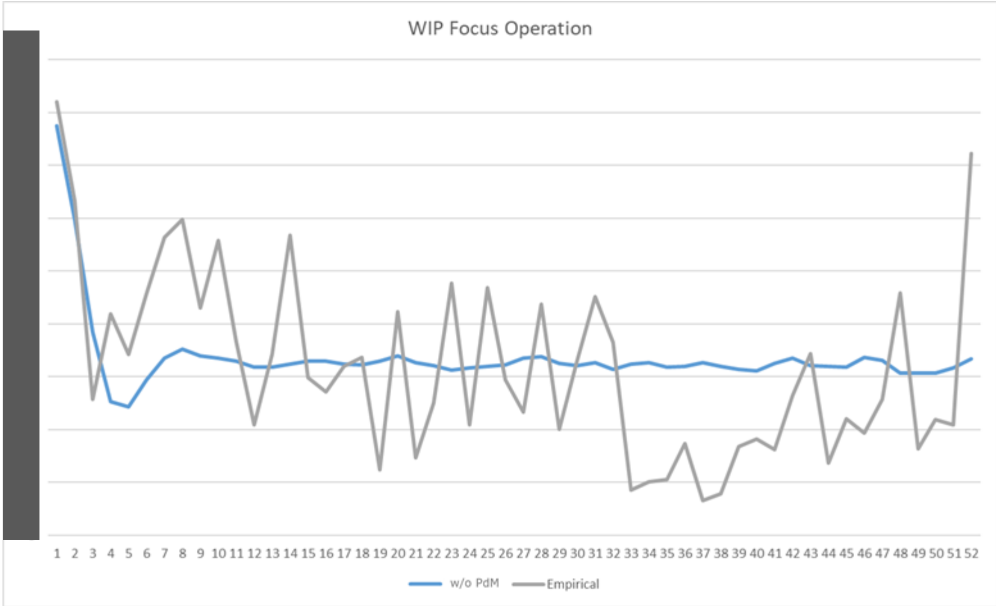


Figure 8-20: Empirical Validity of WIP at Focus Operation

Although the courses between simulation and historical data do not match exactly, the dimension and average trend of the simulation results are valid except for a few outliers that are not predictable.

2) **Compare dimension and development of FF at focus operation**. Figure 8-21 shows the visual comparison of simulated and empirical values from another operation. The blue line refers to the simulated results without application of PdM, whereas the grey line represents the empirical data for FF at the selected operation. The actual values are not allowed to be published since they depict confidential information about the company performance.

At the first glance, the simulated FF and the FF from the empirical data show significant differences for the selected operation and period. These differences are mainly caused by oscillations that exist within the historical data and that cannot be predicted by PdMSM mainly because of noise. However, the dimensions are comparable and the trends show similarities such as higher values in the first third of the period and decreasing values in the last third.

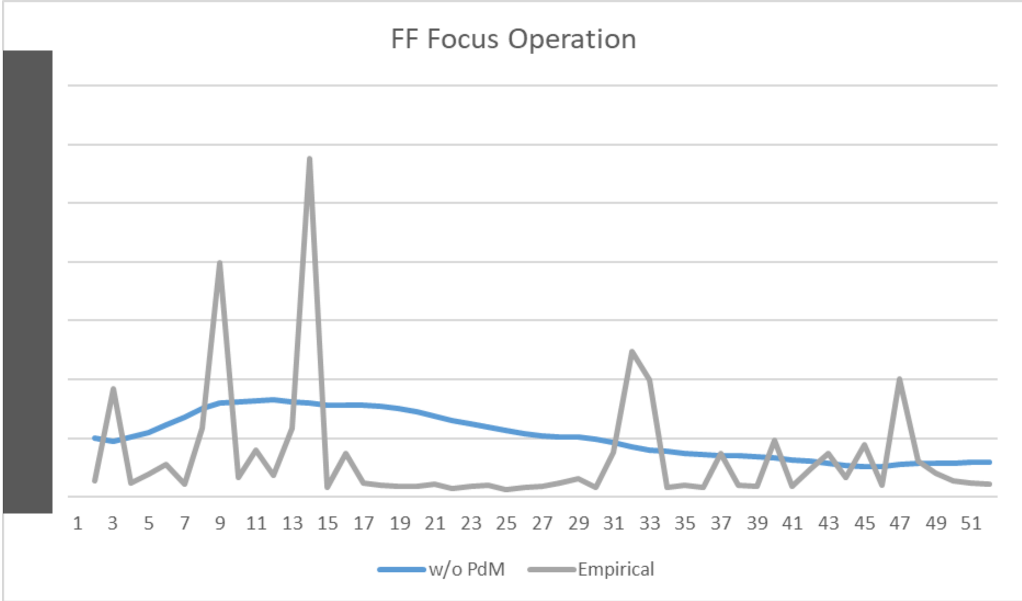


Figure 8-21: Empirical Validity of FF at Focus Operation

3) **Compare dimension and development of unscheduled downtime at selected workcenter**.

Because the term 'workcenter' refers to a set of machines, the historical data that is stored at machine-level must be aggregated. The comparison data uses the weekly average of unscheduled downtimes over six machines that belong to the same workcenter. The historical unscheduled downtimes are then cumulated over one year. Figure 8-21 shows the visual comparison of simulated and empirical values. The blue line refers to the simulated results without application of PdM, whereas the grey line represents the empirical data for unscheduled downtime at the selected workcenter.

The figure demonstrates that dimension and final values of the both simulated and historical UD is similar though the starting points and slopes are slightly different. Again, the actual values are not allowed to be published since they depict confidential information about the company performance.

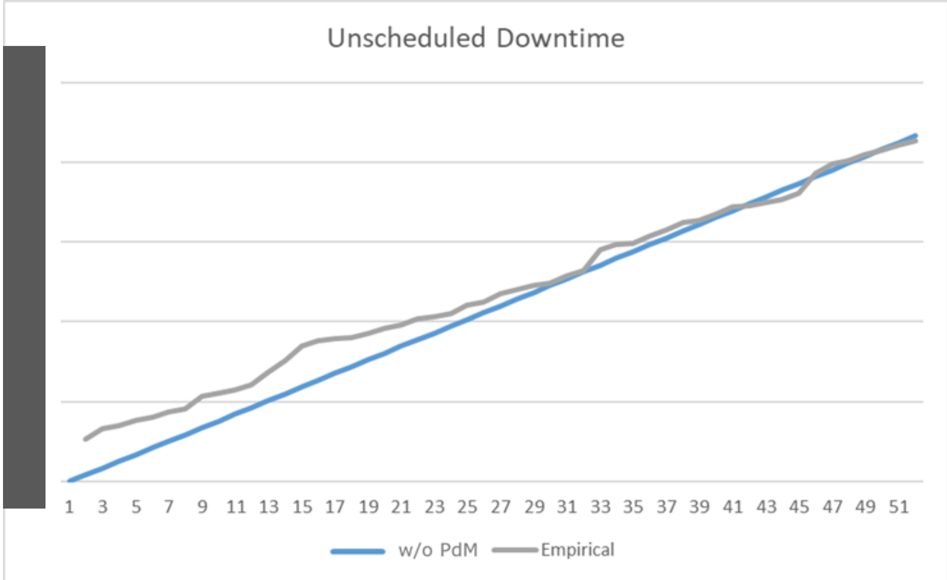


Figure 8-22: Empirical Validity of Unscheduled Downtime at Selected Workcenter

These results support the empirical validity of the model because the dimension and trend of selected simulated values are consistent with the real production system over one year.

8.6.5 Application Validity

The model must be capable of supporting the method that was defined in Section 8.2. Therefore, the application validity must be verified by executing the method that uses the model and its results.

1) **Identify a high-volume product and gather data for model initialisation**

The model requires a detailed level of initial configuration in the context of a selected product. To verify the correctness of the simulation model, a high-volume product from the case study company is selected. The test environment consists of information about the product route from the FoL production area including its operations and workcenters. Furthermore, the planning data, such as RPT, expected cpk, expected failure rate or expected MTTR, are required for those operations and workcenters that are focussed on during the experiment. To configure the production-line sub-model, the historical performance data is also required to specify the average CT, batch size and WIP. For the operator sub-model the expected number of operators, as well as the planned operator availability, are crucial for the initialisation. All types of data that are required to initialise the model are either retrieved from the databases that were discussed in Section 5.5, or must be configured based on expert assessment for soft information.

2) Select operations that shall be compared

The test case compares two operations from a selected product route to evaluate which one would generate more benefit over one year when PdM has been applied. The route consists of 133 operations. The first operation performs an evaporation process that is released to four machines; the second operation performs a sputtering process that is released to three machines. Although both operations belong to the workshop ‘metallisation’ and the process goal is to add layers of one or many noble metals to a wafer, the single process execution as well as the equipment complexity is quite different. The evaporation operation uses machines that load a number of wafers from one or many lots – the batch size – into one big chamber and processes them in parallel. The operation ends for all wafers at the same time. By contrast, the sputtering operation requires cluster machines that consist of up to six chambers. Each chamber can only process one wafer at the same time. A handling robot moves the wafers one by one from the loading station into the desired chamber to perform the process. After the process has finished, the handling robot moves the wafer either to the next chamber to add another noble metal layer or back to the loading station when the process goal is achieved. The operation ends when all wafers from a lot have achieved the process goal. Due to the machine complexity, each sputter chamber can have downtimes independently, but the machine is still ready for production but with less capacity. Therefore, each chamber stores its own set of status data in the CIM database and the amount of historical data is significantly higher compared to the evaporation machines.

3) Identify goals of PdM

A simulation user must be aware of the performance indicators that shall be analysed and compared to evaluate the benefits of PdM. For this simulation model, twelve performance indicators from different sub-models were selected. The selected indicators are dynamic variables or stock variables. To export the simulation data into an Excel file that is accessed through an AnyLogic connector, it is necessary to create and configure a dataset per variable. AnyLogic writes the weekly results of each variable during the experiments into its associated dataset. Each experiment requires two runs. The first run has deselected the 'PdM Active' flag to indicate a manufacturing process under normal conditions. The second run has activated this flag to enable the impact associations through PdM in all sub-models. After each run, the user must press a button to trigger the data export into Excel. Figure 8-23 shows the components that are required to process this data export including the selected datasets.

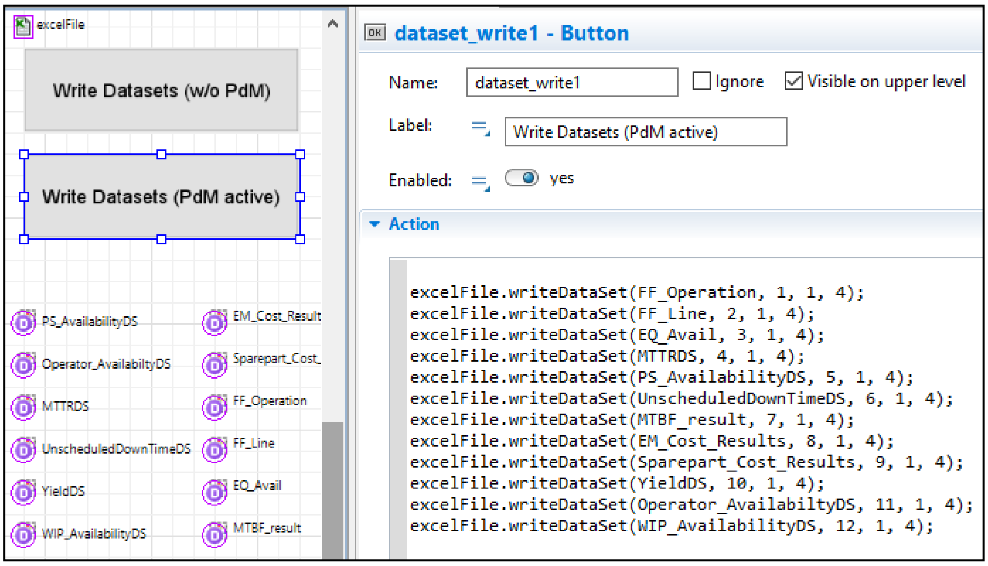


Figure 8-23: Data Export Configuration for Experiment Results

4) Initialise and execute experiments

To compare the selected operations, an initialisation file per scenario is created and configured for each parameter that was discussed in Section 8.5. Since the configuration values depict confidential information, they are not allowed to be published. More details about the manufacturing process and the use of sputtering and evaporation are presented in Section 5.4. Table 8-10 shows the configuration for all sub-models of the sputtering scenario.

Table 8-10: Configuration for Sputtering Experiment

Workcenter	[redacted]		[redacted]
Assist Rate		**Probability Avoid Downtime**	
Failure Rate		**Percentage New EQ Invest**	
MTTR Plan		**Percentage Spare Part Replacement**	
Number Similar Machines		**Repair Improve Factor**	
Equipment Lifespan Planned		**Percentage SD**	
Percentage UD		**Percentage SB**	
Operator			
Number Operators		**External Motivation Factor**	
Degree Qualification		**Number Operators Motivated**	
		Number Operators Unmotivated	
Equipment Maintenance			
EM Staff Min		**EM Staff Opt**	
EM Current		**EM OOS**	
EM Pool			
Product Line			
Fab Utilization		**RPT Prod**	
PreProc CT		**PreProc BS**	
PostProc CT		**PostProc BS**	
Single Process Variety		**Setup Rate**	
Post Proc WIP		**PreProc WIP**	
Focus Op WIP			
Focus Operation			
RPT		**Number Process-released Machines**	
Batch Size		**Percentage Process Inspections**	
4M Synchronicity		**cpk**	
Percentage Wafer to Scrap		**Percentage Expected Volume**	
Percentage Wafer to Rework		**Percentage Machine-rel. Process Failures**	
Target Automation Degree		**Noise Factor**	
Costs			
Cost Rate EM		**Cost Rate Inventory**	
Cost Rate Personnel		**Cost Rate Product**	
Cost Rate Spare Parts			

The same preparation must be performed for the evaporation scenario. Table 8-11 shows the configuration data for all sub-models.

Table 8-11: Configuration for Evaporation Experiment

Workcenter			
Assist Rate		**Probability Avoid Downtime**	
Failure Rate		**Percentage New EQ Invest**	
MTTR Plan		**Percentage Spare Part Replacement**	
Number Similar Machines		**Repair Improve Factor**	
Equipment Lifespan Planned		**Percentage SD**	
Percentage UD		**Percentage SB**	
Operator			
Number Operators		**External Motivation Factor**	
Degree Qualification		**Number Operators Motivated**	
		Number Operators Unmotivated	
Equipment Maintenance			
EM Staff Min		**EM Staff Opt**	
EM Current		**EM OOS**	
EM Pool			
Product Line			
Fab Utilization		**RPT Prod**	
PreProc CT		**PreProc BS**	
PostProc CT		**PostProc BS**	
Single Process Variety		**Setup Rate**	
Post Proc WIP		**PreProc WIP**	
Focus Op WIP			
Focus Operation			
RPT		**Number Process-released Machines**	
Batch Size		**Percentage Process Inspections**	
4M Synchronicity		**cpk**	
Percentage Wafer to Scrap		**Percentage Expected Volume**	
Percentage Wafer to Rework		**Percentage Machine-rel. Process Failures**	
Target Automation Degree		**Noise Factor**	
Costs			
Cost Rate EM		**Cost Rate Inventory**	
Cost Rate Personnel		**Cost Rate Product**	
Cost Rate Spare Parts			

Both experiments are performed with PdMSM based on these parameter values to generate and export the results. After each experiment has been finished, the user must copy the created result file and rename it by an operation-specific identifier. This is necessary because AnyLogic does not allow the creation of new Excel files and requires a template file as connection endpoint. A user is not limited to compare only two operations. Therefore, it is important to manage the result files by name; otherwise, with a bigger number of result files, the contents cannot be associated to a particular experiment in worst case.

5) Analyse and Evaluate results

A result file consists of multiple sheets, where each sheet belongs to one dataset from the experiment. The order is specified in the function body of the data export buttons as shown in Figure 8-23. A sheet consists of two series of data, where the left one refers to the normal execution and the right one to the execution with PdM consideration. By adding a percentage formula to a further column, a user can compare the relative differences for each week. Figure 8-24 shows an excerpt of one of the result files.

	A	B	C	D	E	F	G
1	1	0		1	0		0,00%
2	2	14368,3347		2	14216,16		-1,07%
3	3	28289,2135		3	27812,9451		-1,71%
4	4	42149,1309		4	41323,4343		-2,00%
5	5	55984,5563		5	54798,7905		-2,16%
6	6	69806,6523		6	68254,8924		-2,27%
7	7	83620,3458		7	81698,8033		-2,35%
8	8	97428,2526		8	95134,2918		-2,41%
9	9	111231,929		9	108563,609		-2,46%

Figure 8-24: Sample Experiment Result with two Data Series and a Percentage Comparison in column G

A simulation user can perform experiment-specific analyses with only one result file. For instance, the user wants to understand the development of the unscheduled downtime over a year with and without application of PdM. Figure 8-25 shows a comparison of the UD results for the sputter experiment. Since the simulated values are strongly related to the company performance, they are not allowed to be published.

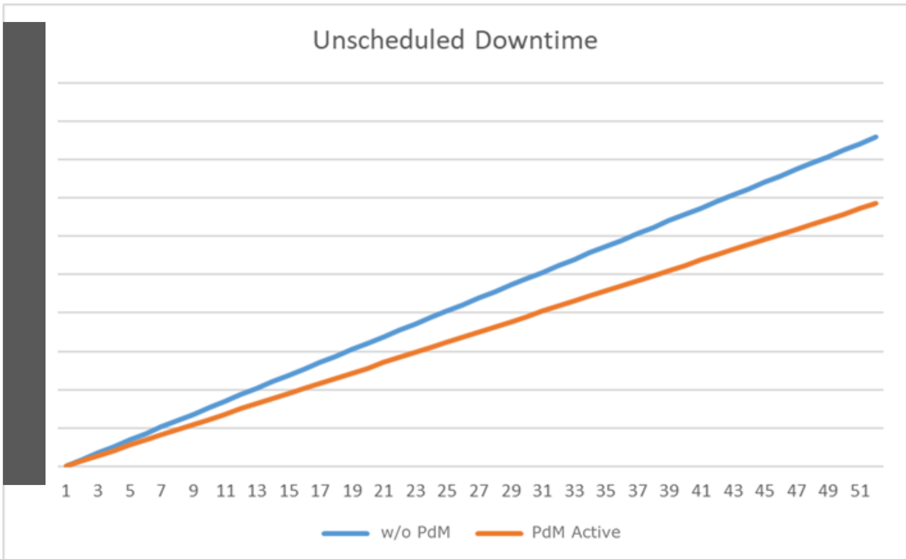


Figure 8-25: Development of UD for Sputter Workcenter

The blue line refers to the normal scenario without application of PdM, whereas the orange line visualizes the development of UD if PdM was applied at the workcenter. The comparison of both time series indicates that the sum of UD over one year would decrease by ca. 15% after application of PdM.

6) Comparison of the results of all experiments

To compare different operations, the user can use the percentage comparison results from each file and merge them into a new analysis document. Figure 8-26 shows how the equipment availability of sputtering and the evaporation workcenters would change after the application of PdM.

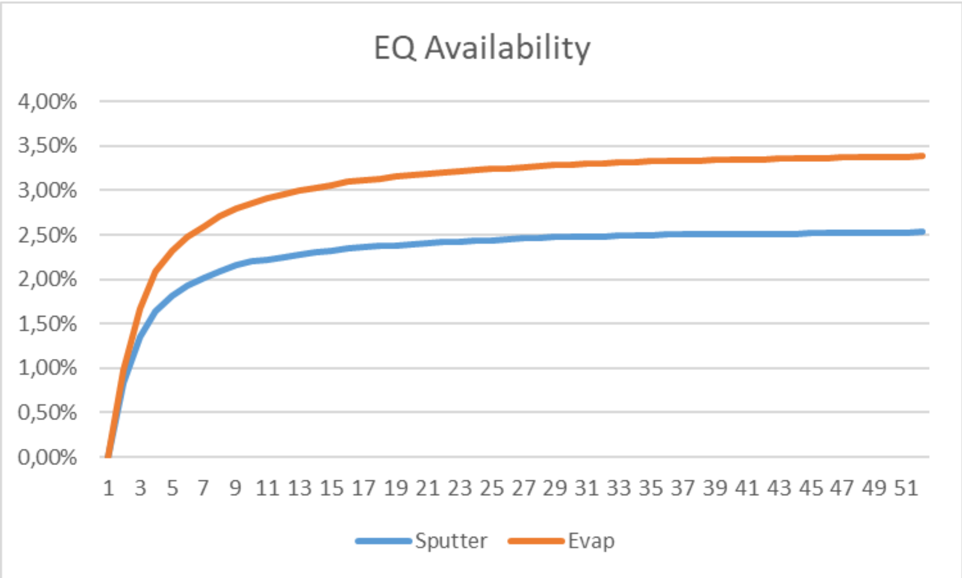


Figure 8-26: Comparison of Sputtering and Evaporation regarding Equipment Availability Evolution after PdM Application

From Figure 8-26, it can be seen that the equipment availability at the evaporation workcenter would improve approximately twice the sputtering workcenter with a continuous rate over the year. To understand the influence of PdM application on the performance of the focus operations, the flow factor development can be compared as shown in Figure 8-27.

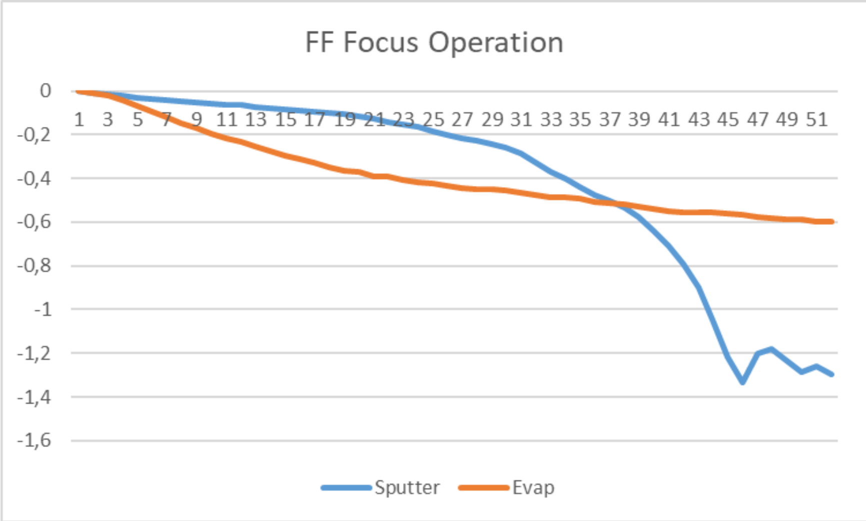


Figure 8-27: Comparison of Sputtering and Evaporation regarding Product Line FF Evolution after PdM Application

The figure shows that the performance of both operations would improve by the application of PdM. By end of the simulated year, the sputter operation would have improved the most, whereas the evaporation operation would have the largest benefit until week 38. Another aspect is to compare the influence of PdM application on the overall product line performance between the selected operations. Figure 8-27 depicts this type of comparison for the selected operations.

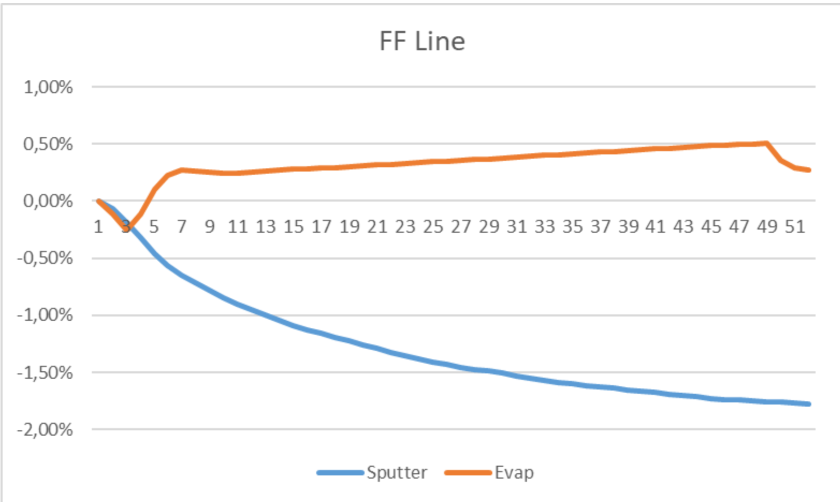


Figure 8-28: Comparison of Sputtering and Evaporation regarding Product Line FF Evolution after PdM Application

The result is that the performance of the whole product line would decrease marginally over time if PdM was applied at the evaporation workcenter. By the application of PdM at the sputter workcenter, the entire product line performance would increase over time.

7) Identify preferable workcenter

The analysis reveals that the PS performance would improve most significantly by applying PdM to the sputtering workcenter. This improvement is effective to the specific operation as well as to the entire product line. In contrast, the evaporation equipment availability would increase at most when applying PdM. A production manager must choose the preferred workcenter depending on the previously selected goals. If only the equipment performance improvement is the target, it is worth applying PdM to the evaporation machines. If the logistics aspects are considered in order to improve the entire product line performance, the results suggest applying PdM to the sputtering workcenter.

This sub-section has demonstrated the application validity by describing the application of the method using the developed model in detail. The discussion has included: how to define a scenario, how to initialise an experiment, how to export experiment results, and how to analyse and compare the results in order to identify the workcenter where PdM would generate the most significant improvements for the SI PS performance.

8.7 New Knowledge from Experiments

The experiments have demonstrated that the quantitative benefits of PdM application are dependent on the selected operation and workcenter. Whereas the PPES provides a general and qualitative trend for direct and transitive influences of PdM on the SI PS performance, the PdMSM allows a more specific differentiation. There are differences between product lines, their operations and the workcenters that are used to process the operations. These details must be considered in order to analyse the quantitative influences of PdM. Besides the expected effects that were mentioned by experts or inferred by PPES, the experiments have revealed new findings regarding the application of PdM in SI that are discussed as follows.

1) PdM leads to reduction of downtimes and failures, but not necessarily to the reduction of MTTR.

The simulation results show that MTTR grows when PdM is applied, although downtime and number failure decrease. This effect is contradictory to the expert interview results and PPES. Figure 8-29 shows the effect for the evaporation experiment.

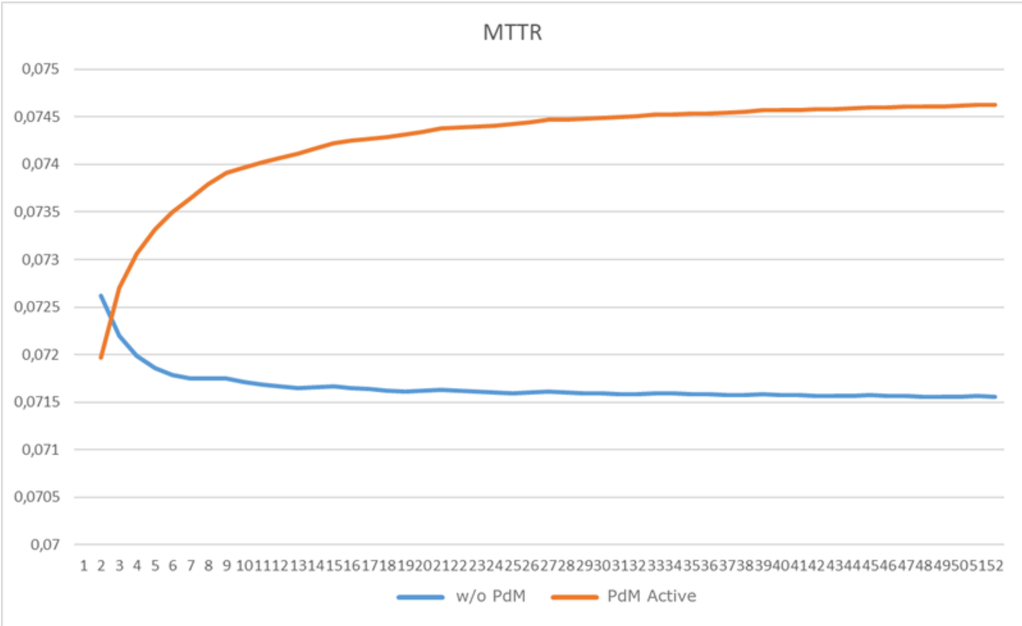


Figure 8-29: Results for MTTR

An analysis of the detailed simulation results suggests that this effect comes from a disproportionate development of repair time and the number of failures. These elements are the required elements for the MTTR calculation. Although both the sum of repair time (ca. −29%) and the number of failures (ca. −33%) over a year are reduced significantly by application of PdM, the number of failures decreases by a higher factor compared to the repair time. This is why the MTTR increases in this situation. Technically, this effect is produced due to the independence of the flows in PdMSM that add failures and UD. Practical reasons for this effect can be the insufficient balance of EM availability between the production shifts or the reduction of EM staff because of PdM. In such cases, also fewer failures can take longer to be repaired. The new insight is that a disproportionate reduction of failures and repair times must be averted when applying PdM in order to reduce MTTR.

2) While PdM improves the Equipment Availability and Equipment Capacity, it could increase the Flow Factor (operation and line).

Several experiments have demonstrated that the application of PdM at both selected operations would increase the flow factor of the product line – which is a negative effect – under certain conditions. Figure 8-30 shows the flow factor development for a scenario where the parameter ‘Expected Volume Percentage’ is increased from 0.1 to 0.2 for both operations. This modification increases the reserved capacity of the underlying workcenter for the selected operation and product line.

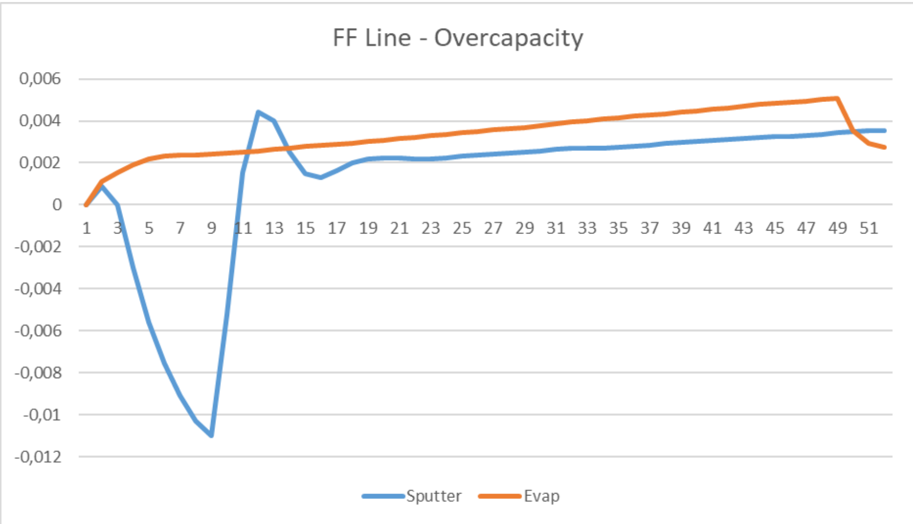


Figure 8-30: Comparison of Sputter and Evaporation Operations with Negative Effect on PS Performance after PdM Application

A similar consequence appears for the focus operation itself. This effect does not meet the expectations of the interviewed experts. An analysis of the simulation environment reveals the WIP at the focus operation as a limiting cause. Although the operation including all PS participants could potentially perform faster due to PdM, there is not enough WIP available to turn this improvement into a real performance benefit. Figure 8-31 shows the results of WIP availability before and after PdM is applied for the evaporation operation.

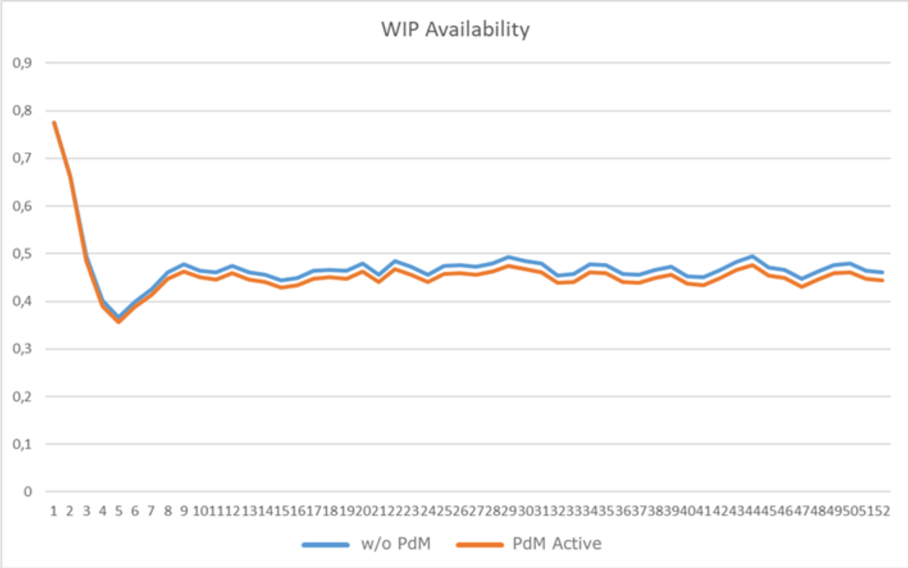


Figure 8-31: Results for WIP Availability

Further simulation runs with different configurations suggest that this effect only appears for operations that are processed with workcenters where overcapacity exists. When PdM is applied, the degree of overcapacity increases. In addition, the WIP availability decreases, and therefore, the operation performance decreases as well. When the capacity limit is reached permanently, the initial flow factor is already significantly higher. This can happen, for instance, in case of 'tool dedication' when only one machine is available for a certain process as part of the operation. To demonstrate this effect, the evaporation experiment from the application validity test is limited to three instead of four process-released machines. The initially higher flow factor can be improved by applying PdM because of the increased workcenter capacity. Figure 8-32 shows the FF evolution for both scenarios under limited capacity: the experiment indicates that the average FF would decrease by almost 50% due to application of PdM in this situation.

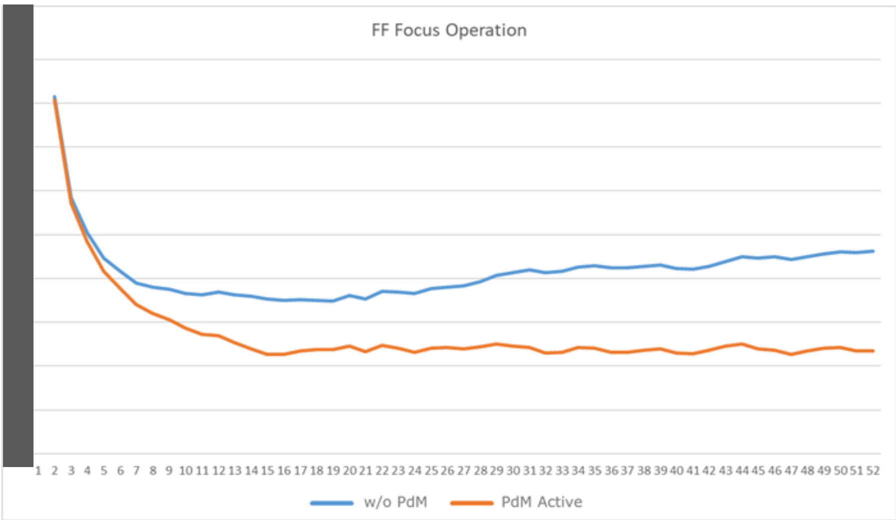


Figure 8-32: Results for Flow Factor at Focus Operation with Limited Capacity

The WIP availability is constantly equal to one, because there are permanently more wafers waiting to be processed than the workcenter is able to serve. The application of PdM does not reduce the WIP availability in this case, as shown by Figure 8-33.

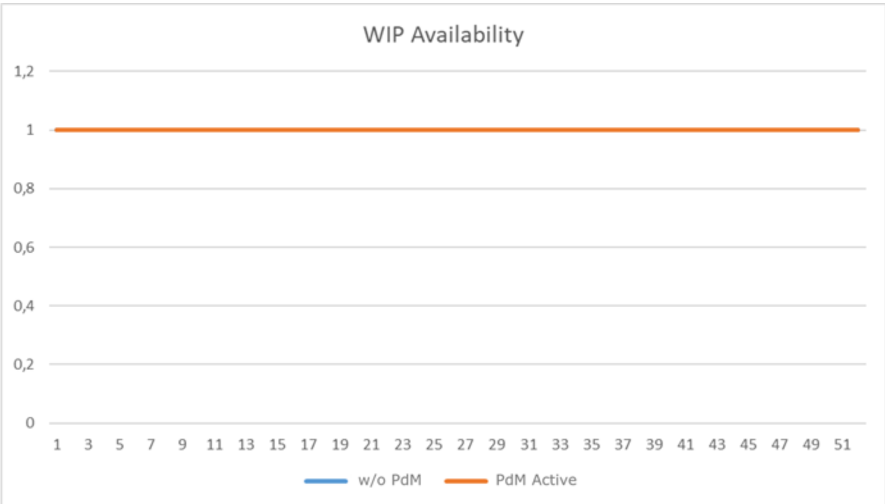


Figure 8-33: Results for WIP Availability at Focus Operation with Limited Capacity

This new finding supports model users in order to select proper operations. PdM provides only benefit to the PS performance, if the associated workcenter is limited in capacity.

3) Percentage of EM-related cost reduction that is triggered by PdM is dependent on spare part lifespan.

EM costs and spare part costs are mainly affected by the application of PdM compared to other types of costs. The comparison in Figure 8-34 shows how PdM would reduce both types of costs over one year.

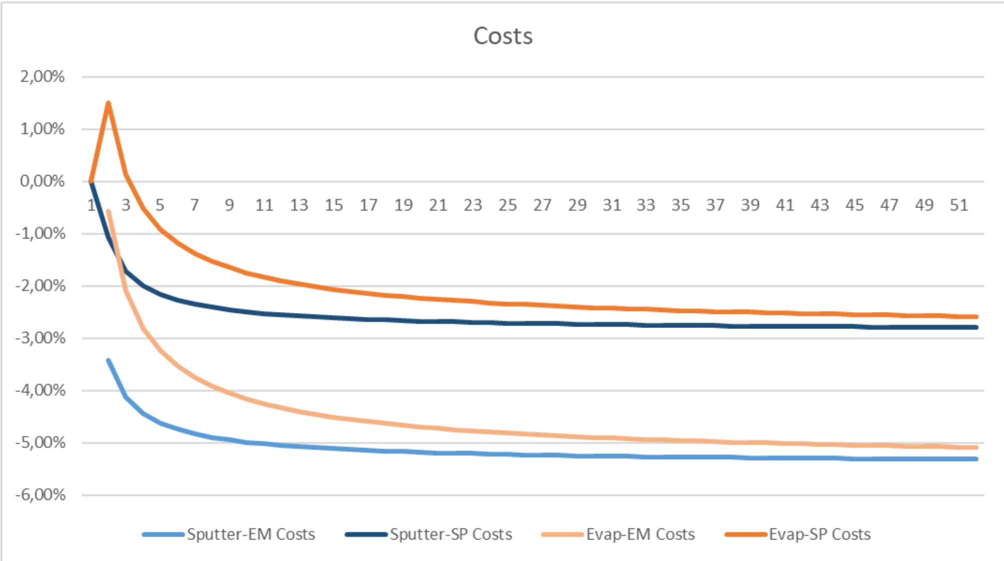


Figure 8-34: Comparison of Influences of PdM on EM and Spare Part Costs

Despite an early outlier in the development of the spare part costs for evaporation equipment, the courses of the lines are similar. Because the percentage differences are calculated based on stock variables, which do not have any subtracting flow, the final values consider the sum of costs from the entire simulation horizon. The figure depicts that PdM would reduce both costs by a higher percentage when applying at the sputter operation. It should be considered that the weekly cost rates are different for both operations in the experiments. The sputter operation generates much higher spare part costs, whereas the evaporation generates more EM costs. Further experiments were executed to understand the dependencies, for instance, with equal cost rates. However, the height of the weekly costs does not influence the percentage difference that can be achieved through PdM. Finally, the degree of exhausting wear limits was identified as the root cause for this result. Figure 8-35 shows the percentage differences for both operations when PdM is applied.

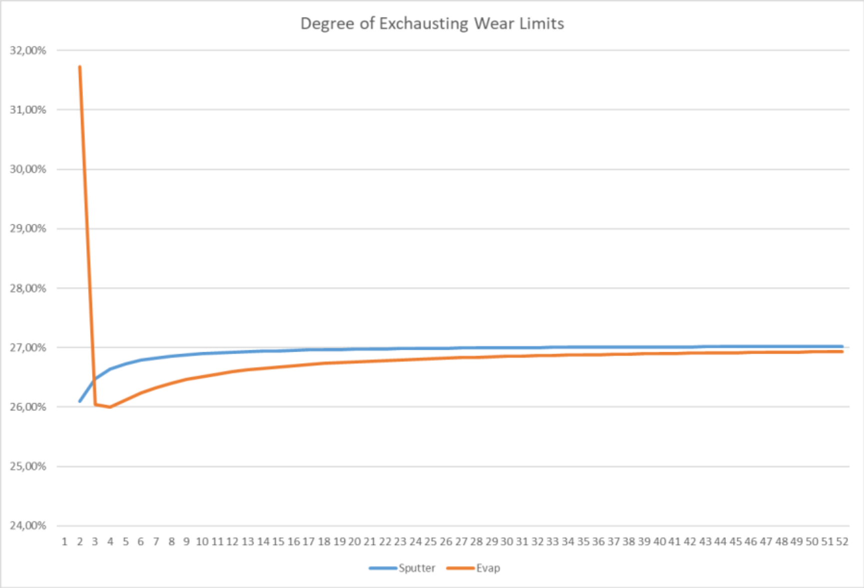


Figure 8-35: Comparison of the Degree of Exhausting Wear Limits when applying PdM

Caused by other influences within the workcenter sub-model such as failure reduction, the degree improvement is slightly higher for the sputtering operation. The new insight is that the percentage cost reduction is independent of the absolute costs. If a PdM project is initiated to reduce costs and the cost rates of the potential production areas are similar, the area with the highest percentage of improvement of exhausting wear limits shall be selected. However, if the cost rates are different, it is crucial to calculate the absolute cost reduction based on the percentage improvement in order to select the preferable area.

4) Degree of yield improvement by application of PdM is dependent on the current scrap rate at the focus operation.

Experts have stated that they believe that the yield increases by the application of PdM. However, it was not clear from the primary data or the PPES under which conditions the yield would improve at most. Figure 8-36 shows a comparison of the two operations sputtering (blue line) and evaporation (orange line) based on results from the application validation. The figure depicts the percentage yield improvement that is generated by applying PdM per operation.

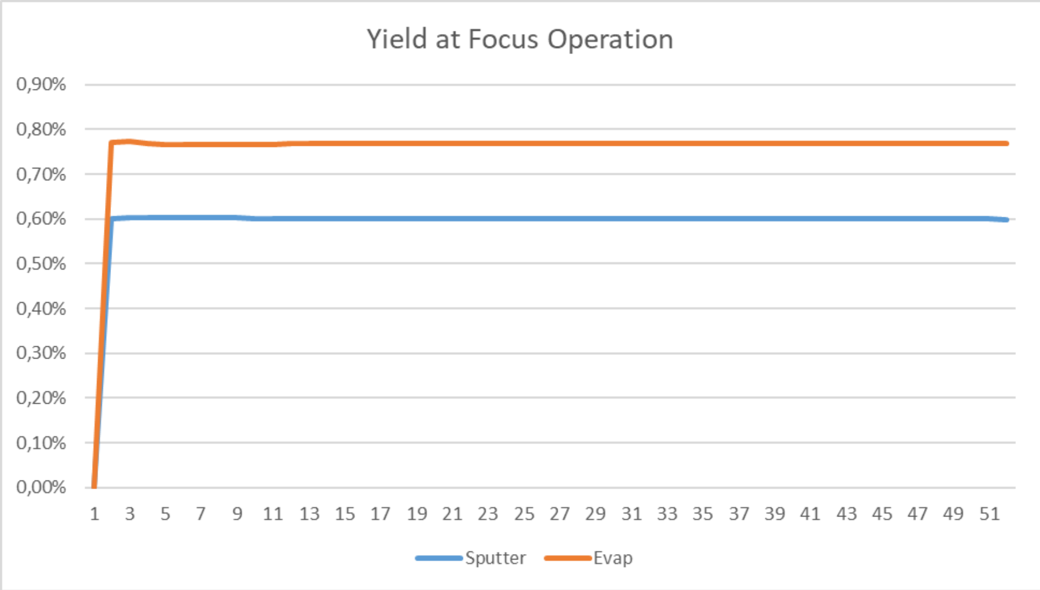


Figure 8-36: Yield Improvement Comparison between Sputtering and Evaporation when PdM is applied

Further experiments under varying conditions have been executed to confirm or refute, for instance, the percentage of machine-related process failures or the WIP level at the pre-process as influencing factors. Finally, the root cause for this effect could be found at the higher initial scrap percentage at the evaporation operation compared to sputtering. The new insight is that the degree of yield improvement gained by PdM is not static but dependent on the operation scrap rate. If yield improvement is the goal, priority within a PdM project must be given to those workcenters whose associated operations have a comparatively high scrap rate.

5) PS Availability does not increase necessarily but potentially decreases by the application of PdM.

Similar to the flow factor finding, the PS availability can only be improved by the application of PdM when the capacity at the workcenter is limited. This effect occurs at least if the four partners are synchronous. However, the partners are not necessarily synchronous in a real SI PS. In such situations, the PS availability is lower than in a synchronous environment and this leads to poor manufacturing efficiency. To understand the consequences under different circumstances, Figure 8-37 provides a comparison of the results of four experiments. It should also be noted that the initial PS availabilities of each experiment without application of PdM are also different.

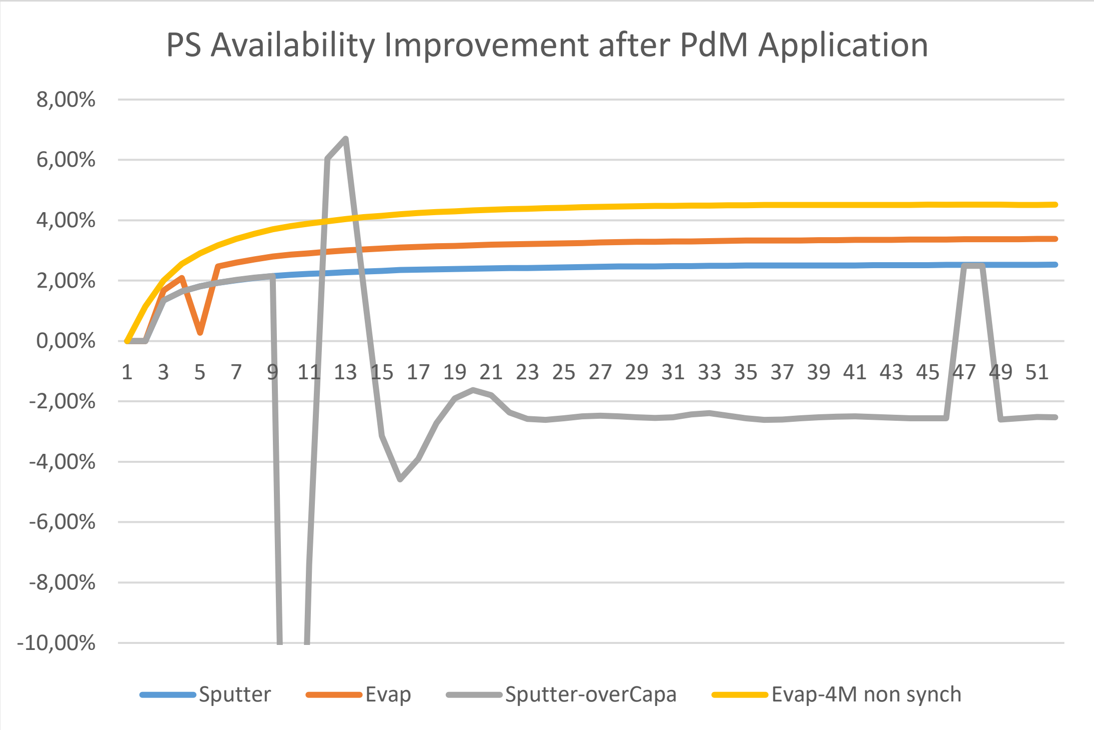


Figure 8-37: PS Availability Comparison under Capacity Consideration after PdM Application

The blue and orange lines show the percentage differences in PS availability if PdM is applied for sputtering and evaporation operation. The figure shows that the availability generally increases for these two scenarios (by approx. 2.5 to 3.2%), and therefore, PdM has a positive effect. The grey line refers to the experiment where sputtering has an increased capacity for the selected operation, which leads to overcapacity without an increased production volume. In this situation, the application of PdM would improve the PS availability during the first weeks; however, it mostly decreases for the rest of the year, which is a negative effect on the PS performance. Generally, this particular experiment shows oscillations in the PS availability with and without the application of PdM; this is why the percentage differences that are depicted by the course of the grey line are strongly fluctuating. The results verify that PdM can improve the PS availability only in capacity-limited environments. The yellow line refers to an experiment where the evaporation uses the same configuration as for the orange line, except for the four partners that are not synchronous. The results suggest that PdM would provide the most significant percentage improvement in this situation. Regarding PS performance, the analysis leads to three new insights:

1) The application of PdM improves the PS availability of an operation under capacity restrictions even if the four partners are synchronous.
2) The application of PdM improves most effectively the PS availability of an operation where the four partners are non-synchronous.
3) The application of PdM decreases the PS availability of an operation where overcapacity exists.

These insights must be considered when an operation or workcenter is selected for a PdM project with the goal of PS availability improvement.

8.8 Summary

This chapter has discussed the quantitative analysis and evaluation of impacts of PdM on the PS performance in SI under the consideration of attributes and dynamics of a real production environment. A method was defined that supports SI companies in the identification of a preferable workcenter where the application of PdM generates the most significant benefits for the PS performance. In order to develop a valid simulation model, the model scope and considerations were specified as prerequisites for the development process. The model development process transformed CLM elements into SD variables that participate in six interacting sub-models. Each sub-model is concerned with a specific aspect when evaluating the benefits of PdM for SI PS performance. All variables are connected through differential equations, which were discussed as part of the development process, or algebraic equations, which are listed in the appendix A3. In addition, the development of the simulation user interface was discussed.

To prove the validity of PdMSM, several established test procedures were executed and passed. The test procedure ‘application validity’ described in detail the application of the method based on PdMSM in order to compute and evaluate the benefits of PdM for particular scenarios. It was demonstrated that the method allows the identification of preferred operations from a product line where PdM should be applied in order to generate the most significant benefits for the PS performance. Finally, new knowledge has been presented to differentiate the quantitative influences of PdM application on the SI PS performance under special circumstances, such as overcapacity and synchronisation of the four partners. These insights demonstrate that there are also situations where the application of PdM may worsen the SI PS performance. With its presented capabilities, the method based on the PdMSM solves RO4.

Chapter 9 Conclusions and Further Work

9.1 Main Achievements

This section summarizes the main achievements from this thesis according to the initially formulated RQs.

RQ 1: What is the current state in research on simulating and evaluating the production system performance in SI?

The semi-systematic literature review presented a concise view on applications, parameters, calculation types and structural flexibility of PMs that are proposed for SI PS. The underlying core methods that are used within those models can be classified as analytical, deterministic, statistical, ML-based and others. The reviewed models are employed with challenges from automation, logistics, quality, setup and maintenance as well as patterns and causal relationships. The models are able to predict performance indicators of SI PS such as work in progress, cycle time, wait time and going rate.

The review has also discovered that none of those models can be applied to investigate PS behaviour from the perspective of PA. Due to the selected type of calculation, most of the models are not extendible to serve scenarios other than those initially intended. The model review has further shown that the fundamental associations and effects between PA and SI PS performance have not yet been analysed. This result supports the importance of this study, which is explicitly employed to investigate the impact of PA on the performance of PS in the SI.

RQ 2: Which are the performance-critical characteristics of an SI PS, how are they causally related, and how are they affected by application of PdM?

As preparation for answering this question, two groups of experts where interviewed: IE and EM experts. The raw data was transformed into a common CLM. This CLM consists of records that indicate which source term has an increasing or decreasing impact on a target term including the impact’s weight. A term can be any PS characteristic or aspect of PdM. By transforming this CLM into a diagram, the causal relations between the terms are visualized as a network, which indicates the existence of transitive relations. The direct benefits that PdM might facilitate were pointed out, such as the reduction of machine downtimes or the increased coordination of maintenance processes. However, according to the IE and EM experts, PdM would not directly help to avoid machine downtimes. Based on the number of occurrences in impact associations, the most directly influenced terms as well as the most directly influencing terms were discovered. Although the IE experts did not believe that PdM would directly affect the PS performance, the causal loop relationships revealed high occurrences of flow factor, cycle time, and going rate as target terms within all captured associations. These are the main performance-critical characteristics of an SI PS that must be investigated regarding influences of the application of PdM.

RQ 3: Can a knowledge-based system be developed to compute the transitive or even contradictory impacts of PdM on SI PS performance qualitatively?

Based on the results of RQ 2, a knowledge-based system been developed. The development process showed the importance of exactness in defining core terms and their mutual relationships. An inference engine that is part of a knowledge-based system requires specific information about the inner logics of more complex terms. An ontology tree was developed to model similarity between concepts. By applying object properties, complex terms could be divided into logically dependent concepts and influences between concepts as captured in the CLM could be configured. Concepts, ontology tree and object property associations between concepts build the framework of the PPES. This framework defines the participants of the model and their fundamental relations.

Each direct effect between concepts was formulated as SWRL rule. Special rules were created to describe the logics of transitivity for PPES. These rules are essential to gain results for transitive effects between concepts through the inference engine. The PPES calculated 34 transitive effects, such as that PdM increases the yield or decreases the product costs. These effects where not stated by the experts and are, therefore, considered as new knowledge. In addition, contradictory effects have been identified where transitive paths within the ontology lead to conflicting associations between two selected concepts. The identified contradictory effects are the influence of PdM on:

- Equipment utilization
- Little’s Law (which indicates that the metrics behind the formula would improve)
- Production system variability (also known as ‘Alpha PS’)
- Speed of reaction in case of a machine failure

The identification of contradictory effects represent new knowledge in addition to the expert interview results. With its capabilities as expert system, properly modelled contents and the evaluated results, PPES answers RQ 3.

RQ 4: **Can a simulation model be developed to quantify the impacts of PdM on SI PS performance over time under consideration of particular workcenters, operations and production line characteristics?**

To gain reproducible results, a method that supports researchers and SI companies in applying the PdMSM was defined and explained. The method described the process of data gathering, model configuration and execution as well as result evaluation. The PdMSM development process transformed CLM elements into SD variables that participate in six interacting sub-models. Each sub-model is concerned with a specific aspect when evaluating the benefits of PdM for SI PS performance. All variables are connected through differential equations or algebraic equations that consist of the impact values provided by the interviewed experts.

The model can be applied to differentiate the quantitative influences of PdM application on the SI PS performance under special circumstances. The newly created knowledge can be summarized by following statements:

1. ’Mean Time to Repair’ decreases only if EM managers ensure that PdM supports proportionate reduction of failures and repair times.
2. Logistics performance improves only if the underlying workcenter is limited in capacity or the four partners are non-synchronous.
3. PdM supports optimal cost decreases for workcenters where the degree of exhausting wear limits can be most effectively improved.

4. The degree of yield improvement gained by PdM is dependent on the scrap rate of the operations that are associated to a particular workcenter.
5. If a workcenter has overcapacity, PdM will potentially worsen the logistics PS performances, even if the particular workcenter performance can be improved.

It was demonstrated that PdMSM allows the identification of workcenters in a product- and operation-specific context where the application of PdM would generate the most significant benefits for the SI PS performance. In addition, the experiments demonstrated that there are situations where the application of PdM would reduce the SI PS performance. These results based on the PdMSM answer RQ 4.

9.2 Contributions to the New Knowledge Generation

The literature review results indicate a growing importance of PA and PdM in particular in the area of semiconductor manufacturing. This finding supports the significance of this research. The overall aim of this research was to analyse and evaluate the impacts of PA on the PS performances in the SI. The following are the **key contributions** of this thesis:

1) The thesis proposed a new framework to discover in which way PA can be applied in order to overcome challenges in SI value chains. This perspective of benefit evaluation in the area of PA was not present prior to this project. The framework can be adopted by other research projects in the area of PA and SI.
2) The thesis contributes with the PPES in order to support researchers and practitioners in discovering transitive effects within SI PS qualitatively. Through the analysis and evaluation of the PPES, 34 transitive positive as well as 4 contradictory effects were identified. This result confirms hypothesis 1 that was stated in 2.6 for PdM as particular PA application. The inference engine of the PPES provides valuable explanations why pairs of concepts can have contradictory associations that are both true. This type of knowledge was not present prior to this study. In addition, it was proved that PdM is able

to support SI companies in mastering challenges in SI value chains as proposed by the conceptual framework.

3) Since previous studies in the area of PdM in SI did not consider performance effects beyond machines, a differentiation of advantages and limitations of PdM regarding the various aspects of PS performance was not existing prior to this study. Hence, a further key contribution of this thesis is the generation and presentation of this new knowledge based on simulated dynamic effects in accordance to behaviours from a real SI PS. The results that were generated through PdMSM confirm hypothesis 2 for PdM: it was proved that the benefits of PdM regarding SI PS performance are not static but dependent on particular workcenters and operations in the context of a specific production line. In addition, the experiments revealed scenarios where the benefits of PdM would gain the most significant improvements, where the benefits are limited or where the application of PdM would even decrease the PS performance (e.g., made visible by increased flow factor or decreased PS availability).
4) A practical key contribution of this thesis is a method based on PdMSM to discover, quantify and evaluate the impacts of PdM on the SI PS performance over time under consideration of workcenter-, operation-, and production-line-specific characteristics. Due to the extensive efforts that are required to build a PdM solution for particular machines, it is important to select suitable workcenters where the benefits of PdM are optimal. The method enables a company to differentiate the benefits of PdM based on environmental characteristics such as raw process time, number of similar machines and WSPW. By applying the method, different workcenters can be compared to understand which one would generate the most significant benefit for the SI PS performance if it would be managed through PdM. Criteria for the preselection of operations and associated workcenters as well as considerations for intended goals have been discussed in Section 8.7.

Further contributions of this thesis can be divided into theoretical work and practical applications. Following contributions are mainly associated to **theoretical work**:

1) Primary challenges of SI value chains have been identified and evaluated based on topical research in this area. In addition, the current and potential future implications of the Covid-19 pandemic on SI have been studied and presented.
2) Major issues in the theoretical definition of PA have been detected and discussed. These issues include among others an unclear demarcation from DM and a mismatching selection of PA techniques. It was concluded that a benefit cannot be calculated neither for PA in general nor for a particular PA method. Instead, it was suggested to calculate the benefit of PA based on particular PA applications.
3) Crucial PA applications that are relevant to semiconductor manufacturing have been identified and collected. The thesis contributes with a critical review of current research activities that are concerned with these applications. The detected issues per PA application can be consolidated as follows:
    a. Though **PdM** is an established term, it is not commonly defined in literature. In addition, PdM as a strategy is not clearly related to other maintenance strategies. Existing studies that evaluate the benefits of PdM in general and for particular machines did not consider logistics aspects, though logistics was identified as most challenging area in wafer fabrication.
    b. **SM** is not clearly defined in literature and shows significant overlaps to other PA applications. SM can be considered as a holistic approach that seamlessly integrates multiple PA applications. However, such an approach depends on collaborative standards, which was identified to be a weak spot in SI value chains.
    c. Traditional **process control** consists of multiple applications such as R2R, SPC and FDC, where most of them would improve by application of PA. Though ML outperforms traditional SPC techniques, it is not evident from literature that SI companies migrate to ML-based SPC solutions. Further research is required to understand this reluctance and to develop strategies that support this migration. An additional

finding is that implications of predictive process control on the logistics performance of an SI PS were not studied so far.

d. **PQ** was not commonly defined in literature. Some authors considered it as a result from PdM, though advanced approaches beyond fault prediction were demonstrated and published. Studies on applications that reduce the testing efforts and support quality-by-design have been reviewed. However, influences of PQ on the logistics PS performance were not studied so far. Predictive reliability applications were argued to do not have impact on SI PS performance.
e. **Predictive dispatching** was found to outperform traditional dispatching techniques. Nevertheless, it was not evident from literature that there is a trend in SI to move on towards ML-based dispatching. In addition, **predictive scheduling** shows significant benefits compared to analytical or deterministic approaches. However, it was detected that applications are often called ‘predictive’ without applying PA as considered in this thesis context.

4) The thesis contributes with the presentation of the state of research for PMs in SI. In advance, it was found that the term ‘performance’ was not consistently defined in literature; therefore, a particular definition for the scope of this thesis has been introduced. KPIs that are crucial to SI manufacturing within the defined scope have been presented and associated to selected challenges from SI value chains. Overall, 18 PMs that are capable of predicting influences of various parameters on the SI PS performance have been identified and evaluated. The parameters under study were, for instance, batch size at bottleneck tools, lot size policies, scheduling policies or dispatch-rule parameters. The review process identified different applied calculation types (e.g., analytical and statistical) and different types of challenges (e.g., automation and logistics). Another finding of the review is that none of the examined models is capable of supporting the aim of this research.
5) The majority of researchers in the area of PdM are concerned with benefits of PdM regarding machine performance or by applying

optimal PA methods, e.g., Munirathinam and Ramadoss (2016), Moyne, Samantaray et al. (2016) or Hashemian (2011). Therefore, the general contribution of this study is the presentation of logical associations that reveal how PdM influences the key performance indicators in semiconductor manufacturing beyond machines through transitive causal relationships. These associations are captured within the CLM.

6) Though the thesis discussed only the transitive effects that are found for PdM, the PPES consists of the full picture of logical relationships within a SI PS that are relevant to IE and EM. Hence, it provides also details about transitivity within a SI PS beyond PdM. Overall, 694 transitive relationships were inferred, which can be analysed and evaluated by further research projects. It is believed that PPES and its comprehensive knowledgebase can be applied to any study that is concerned with the logical nature of performance effects in semiconductor chip manufacturing. By developing the PPES with Protégé based on OWL and SWRL as technical foundation, established standards are applied that support the sharing of the results and reusability of the ontology in the science community.
7)

Beyond the theoretical work, the thesis provided following contributions for **practical application**:

1) By applying the PPES to real SI companies, the generated insights may influence decision processes about PdM investments at SI companies. Practitioners can query the PPES to retrieve particular logical dependencies also beyond PdM. This is a valuable contribution due to the complex nature of SI PS, where managers and engineers from different departments are potentially not aware about particular challenges from other areas or conflicts of goals that exist between multiple areas. PPES as a tool may support companies to bring managers and engineers on the same level of knowledge by revealing these conflicts and hidden dependencies from a holistic view.
2) The thesis identified and discussed the most relevant PA applications and capabilities for SI frontend manufacturing: (1) PdM, (2) SM, (3)

predictive process control, (4) PQ, and (5) predictive dispatching and scheduling. The conceptual framework presented the benefits of each application and suggested in which way they can be applied to overcome challenges in SI value chains. IT and production managers can build on these findings in order to define PA strategies and set up appropriate PA projects for their company. In addition, PA techniques that have been verified in literature to gain most promising results for a particular PA application were highlighted. For instance, the 'super learning' approach is proposed to be applied for PdM in order to improve the prediction quality. Data scientists and data engineers at SI companies can use these outcomes in order to decrease own research efforts when implementing a PA solution.

9.3 Limitations and Further Work

Despite the clear research methodology and the various results that contribute new knowledge to the research community that is concerned with PA in SI, there are limitations that need to be addressed. These limitations exist due to the time and resource constraints of the researcher and are discussed as follows:

1) Most of the content of this thesis is employed with the development, analysis and evaluation of models. The primary data for building these models were gathered through expert interviews. It must be highlighted that the model results are only as good as the interviewed experts. Furthermore, most of the experts share years of experience with the case study company. Therefore, it is possible that aspects, associations and challenges, which are specifically relevant to other SI companies, are not sufficiently covered by the models.
2) The application of case study as research strategy provided a snapshot of the SI PS under study including the expectations regarding PdM. Because SI is a fast changing environment and technological capabilities of PA improve rapidly, it is expected that the results of this study have a timely limited validity.
3) The research focussed primarily on PdM although more PA applications exist that are relevant to semiconductor manufacturing as

presented by the conceptual framework. The decision to focus on one particular application was made based on the assumption that a wider evaluation would have exceeded the capacity of a doctoral thesis. The discussed efforts to gather and analyse the primary data regarding EM (see Chapters 5 and 6) and to build and evaluate tools to discover the impacts of PdM on SI PS performance (see Chapters 7 and 8) demonstrate that this assumption was correct.

4) The case study was conducted at a wafer fabrication facility. Therefore, the results of this thesis are mainly valid and applicable for the frontend part of the SI value chain. It is not suggested to apply the results of this thesis to backend PS without further research.
5) The focus of this research was to examine production performance from selected perspectives. The selection of experts that participated the interviews supported this focus. Hence, other performance aspects that are beyond the professional expertise of the interview partners are only covered insufficiently or are potentially missing. During the model development, some of these gaps have been identified, for instance, there is only a small number of causal relations captured that consider operators or costs.
6) Although both PPES and PdMSM support reusability and applicability in practise, their primary audience are researchers. Especially the PdMSM owns some limitations that prevents the direct and efficient application at real SI companies. Generally, it was built using an academic license in AnyLogic, which excludes generating an executable JAR file and commercial use. Therefore, the developed model itself cannot be distributed to SI companies. If a company owns a commercial license of AnyLogic, they can build an own PdMSM based on the provided documentations. However, before applying the model for commercial use, some technical limitations must be solved: (1) PdMSM does only focus on one product line during a simulation run and (2) operations must be selected prior to the actual experiment.
7) From theoretical perspective, the potentially limited accessibility of literature regarding existing PMs or PA applications in semiconductor manufacturing must be considered. PMs from other SI companies could exist that were not published but could be applied to solve this

research aim. Therefore, they could not be reflected in this research. In addition, there could be relevant literature in further libraries that are not accessible via Google Scholar. Though studies from Khabsa and Giles (2014) and Lewandowski (2010) suggest that Google Scholar covers nearly 90% to 100% of all English literature and journals in particular, it cannot be fully excluded that relevant articles are missed to reflect in this research.

Based on these limitations, following further work is proposed that builds on this research project:

1) Further research can be conducted, for instance, in five to ten years to compare the evolutions of both SI and PdM and in which way it affects the results of this research.
2) Further research can be conducted to analyse and evaluate particular impacts of predictive scheduling and other presented PA applications on SI PS performance. The proposed research methodology in this thesis is expected to support other projects as well. The developed tools can be reused for other cases, because they cover the core associations within a wafer fabrication PS. However, it might be required to add other perspectives to the models such as from process engineers or quality engineers for other PA applications.
3) Further research is required to discover specific performance aspects and causal relationships for the backend part. Observations at three SI companies underpin the independency of frontend and backend from logistics perspective (e.g., different units of issue (‘chip’ is the logistic unit in backend, whereas frontend works with ‘wafer’ that consist of thousands of chips); different types of operations and machines; different engineering knowledge). Therefore, it is not suggested to merge backend-specific results into the frontend-oriented knowledgebase that have been developed through this thesis. The transitive and quantified results of merged models would not generate reliable insights. It is proposed to conduct manufacturing performance research in SI for frontend and backend separately.

4) Based on the marginally covered performance perspectives, a proposal for further research is to evaluate the particular impacts of PdM on the socioeconomic aspects of semiconductor manufacturing, which may include employee performance but also social aspects. Another research project could be employed with the analysis and evaluation of detailed cost developments when applying PdM in SI PS. Both PPES and PdMSM can be reused and extended for these purposes.
5) The PdMSM was primarily developed to serve this particular research project. To apply the proposed method efficiently to practice, further work must be spent in order to improve the simulation capabilities. It is suggested that an advanced model should consider (1) multiple product lines that share the same workcenters, (2) multi-operation comparison at the same time within the model as well as (3) merging operation-specific results that refer to the same workcenters. These enhancements would also reduce the manual efforts for data analysis and comparison that is performed in Excel.

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Appendix

A1 IE Data Matrix

#	Source	Type	Target	Numbers of Responses	Impact (Mean)
1	4M Synchronicity	decrease	CT Variance	4	−9
2	4M Synchronicity	decrease	Standby Time Duration	1	−10
3	Alpha Tool	increase	Alpha PS	1	5
4	Batch Size	increase	Alpha PS	1	5
5	Degree of Automation	increase	Importance Of Operator Qualification Level	1	10
6	Degree of Automation	decrease	Operator Qualification Level	4	−6
7	Degree of Knowledge of Engineers about Factory Physics	decrease	Material Flow Variance	4	−5.25
8	Degree of Operator Qualification Level	decrease	CT	1	−8
9	Degree of Operator Qualification Level	decrease	FF	1	−7
10	Degree of Operator Qualification Level	increase	GR	2	4
11	Degree of Production Staff Motivation	decrease	CT	4	−4.5
12	Degree of Unevenness in WIP Distribution	decrease	GR	1	−10
13	Dispatcher Compliance	decrease	FF	1	−3
14	Dispatcher Compliance	decrease	Standby Time Duration	3	−5.33
15	Dispatcher Compliance	decrease	WIP Variance	1	−3
16	Dispatcher Maturity	increase	4M Synchronicity	1	6
17	Dispatcher Maturity	decrease	Standby Time Duration	3	−6
18	EM Availability	increase	Equipment Availability	2	4.5
19	EM Availability	decrease	Standby Time Duration	3	−6
20	EM Availability	decrease	Unscheduled Down Duration	5	−7.6
21	EM Qualification Level	decrease	Scheduled Down Duration	1	−5
22	EM Qualification Level	decrease	Unscheduled Down Frequency	1	−1
23	Equipment Availability	increase	DGR	1	5
24	Equipment Availability	decrease	FF	1	−4
25	Equipment Availability	increase	GR	1	10
26	Equipment Availability	decrease	WIP Variance	1	−3
27	Equipment Going Rate	increase	GR	Math.	Math.
28	Equipment Reservations	decrease	Capacity	1	−3
29	Equipment Reservations	increase	Engineering Time Duration	1	10
30	Equipment Reservations	increase	FF	1	3
31	Equipment Reservations	increase	Standby Time Duration	3	3.33
32	Equipment Reservations	increase	WIP Variance	1	2
33	Fab Utilisation	increase	Downtime Frequency	1	7
34	Fab Utilisation	increase	Scheduled Down Percentage	1	3
35	Flexibility of Operator Qualification Level	decrease	CT	1	−8

#	Source	Type	Target	Numbers of Responses	Impact (Mean)
36	GR	increase	DGR	Math.	Math.
37	High Percentage Process Inspections	increase	CT	3	3
38	Lot Prioritisations	increase	CT Variance	1	6
39	Lot Prioritisations	decrease	GR	2	0
40	Maintenance Strategy	increase	Equipment Going Rate	1	4
41	Maximum Wait Time for Batches	increase	Standby Time Duration	1	2
42	MTBA	decrease	Alpha PS	3	−5
43	MTBF	decrease	Alpha PS	2	5
44	MTBF	increase	Equipment Availability	2	5
45	MTOL	increase	Alpha PS	4	5
46	MTTR	increase	Alpha PS	4	5
47	OEE	decrease	Alpha PS	2	−5
48	OEE	increase	Capacity	1	−5
49	Operator Availability	decrease	CT	4	−6.75
50	Operator Availability	decrease	FF	1	-8
51	Operator Availability	increase	GR	1	10
52	Operator Availability	decrease	Standby Time Duration	5	−3.2
53	Operator Availability	decrease	WIP Variance	1	−4
54	Operator Qualification Level	decrease	FF	1	−3
55	Operator Qualification Level	increase	Flexibility of Operator Qualification Level	2	8
56	Operator Qualification Level	decrease	Standby Time Duration	2	−6
57	Percentage of Bottleneck Equipment	increase	CT	3	8.67
58	Performance Synchronicity of Similar Machines	decrease	FF	1	−5
59	PM Application	decrease	Alpha Tool	4	−6
60	PM Application	increase	Degree Of Production Staff Motivation	1	6
61	PM Application	increase	EM Availability	5	8.6
62	PM Application	increase	Equipment Uptime	5	7
63	PM Application	increase	GR	5	6
64	PM Application	increase	Material Flow	1	10
65	PM Application	decrease	MTBO	2	−5
66	PM Application	decrease	MTOL	2	−7.5
67	PM Application	increase	Scheduled Down Frequency	5	5.4
68	PM Application	increase	Synchronicity Of EM Availability	1	4
69	PM Application	decrease	Unscheduled Down Duration	1	−10
70	PM Application	decrease	Unscheduled Down Frequency	5	−7
71	Process Availability	increase	GR	1	10
72	Process Development at Production Equipment	increase	CT	1	2
73	Process Development at Production Equipment	increase	Engineering Time Duration	1	10
74	Process Development at Production Equipment	decrease	Equipment Capacity	3	−7.67
75	Process Development at Production Equipment	decrease	GR	2	2
76	Process Development at Production Equipment	increase	Unscheduled Down Frequency	3	1.67
77	Process Maturity	increase	Equipment Availability	1	2
78	Process Maturity	increase	Process Stability	4	9.5
79	Process Maturity	increase	Rest 3M Availability	1	8
80	Process Maturity	decrease	Standby Time Duration	1	−2

#	Source	Type	Target	Numbers of Responses	Impact (Mean)
81	Process Maturity	decrease	Unscheduled Down Frequency	6	−5.83
82	Process Stability	decrease	CT	3	−6.33
83	Process Stability	increase	Degree of Automation	1	8
84	Process Stability	increase	Equipment Availability	1	2
85	Process Stability	decrease	FF	1	−4
86	Process Stability	decrease	High Percentage Process Inspections	3	−3
87	Process Stability	decrease	Standby Time Duration	1	−2
88	Process Stability	decrease	Unscheduled Down Frequency	4	−8
89	Process Stability	decrease	WIP Variance	1	−3
90	Process Variety	increase	Scheduled Down Percentage	1	5
91	Processing Time Variance	increase	FF	1	5
92	Rate Efficiency	increase	GR	1	5
93	Rest 3M Availability	decrease	Standby Time Duration	4	−4
94	Rework	decrease	GR	1	−10
95	Scheduled Down Frequency	increase	Alpha PS	1	5
96	SCM Order Patterns Variance	increase	WSPW Variance	1	10
97	Setup Frequency	decrease	Equipment Capacity	3	−4.67
98	Setup Frequency	increase	Importance Of EM Availability	3	7.33
99	Setup Frequency	increase	Scheduled Down Duration	1	5
100	Single Process Variety	increase	Alpha PS	1	5
101	Single Process Variety	decrease	Equipment Capacity	1	−4
102	Single Process Variety	increase	Setup Frequency	3	5.67
103	Tool Dedication	increase	Alpha PS	1	5
104	Tool Dedication	increase	CT	2	7.5
105	Tool Dedication	decrease	Deliverability	1	−10
106	Tool Dedication	decrease	Equipment Capacity	3	−1
107	Tool Dedication	increase	FF	1	−2
108	Tool Dedication	increase	Importance Of Equipment Availability	1	3
109	Tool Dedication	increase	Material Flow Variance	1	10
110	Tool Dedication	increase	Risk of Product Line Down	4	8.25
111	Tool Dedication	decrease	Standby Time Duration	2	−5.5
112	Tool Dedication	increase	WIP Variance	1	8
113	Transportation Variability	decrease	Equipment Capacity	1	−5
114	Utilisation Profile Variance	increase	CT	1	10
115	Utilisation Profile Variance	increase	Percentage of Bottleneck Equipment	1	5
116	WIP Variance	increase	CT Variance	4	4.75
117	WIP Variance	increase	FF	1	−3
118	WIP Variance	increase	Standby Time Duration	1	6
119	WSPW Variance	increase	FF	1	2
120	WSPW Variance	increase	Risk of Equipment bottleneck	3	2.67
121	WSPW Variance	increase	Standby Time Duration	3	4.67
122	WSPW Variance	increase	WIP Variance	5	3.8
123	Yearly WIP reductions	increase	WSPW Variance	1	3

A2 EM Data Matrix

#	Source	Type	Target	Number of Responses	Impact
1	Offline PM application	decrease	Speed of reactions	3	Simulation Config.
2	Offline PM application	increase	Quality of statistics	1	Simulation Config.
3	Offline PM application	increase	Probability to find new failure patterns	1	Simulation Config.
4	Offline PM application	increase	Quality of monitoring	1	Simulation Config.
5	Offline PM application	increase	Quality of planning procedures	2	Simulation Config.
6	Offline PM application	increase	Independence in running analyses	1	Simulation Config.
7	Offline PM application	increase	Transparency in effectiveness of EM activities	1	Simulation Config.
8	Offline PM application	increase	Number of relevant data sources	4	Simulation Config.
9	Offline PM application	increase	Level of understanding of historical failure patterns	3	Simulation Config.
10	Online PM application	decrease	Quality of statistics	2	Simulation Config.
11	Online PM application	increase	Dependency on existing knowledge	1	Simulation Config.
12	Online PM application	increase	Data traffic	1	Simulation Config.
13	Online PM application	increase	Dependency on EM processes	1	Simulation Config.
14	Online PM application	increase	Dependency on algorithm quality	1	Simulation Config.
15	Online PM application	increase	Efforts to prepare data and algorithm	2	Simulation Config.
16	Online PM application	increase	Probability of to avoid failures	2	Simulation Config.
17	Online PM application	increase	Speed of reactions	4	Simulation Config.
18	Percentage of Preventive Maintenance	decrease	MTTR	1	5
19	Percentage of Preventive Maintenance	increase	Speed of analysis	1	8
20	Percentage of Preventive Maintenance	increase	Speed of reactions	1	10
21	Percentage of Preventive Maintenance	decrease	Frequency of Unscheduled Machine Downtimes	1	9
22	Percentage of Preventive Maintenance	decrease	Duration of Machine Downtimes	5	7
23	Percentage of Preventive Maintenance	increase	Quality of planning procedures	1	3
24	Percentage of Preventive Maintenance	increase	Probability to avoid late effects	1	7

#	Source	Type	Target	Number of Responses	Impact
25	Percentage of Preventive Maintenance	increase	Probability to avoid collateral damages	1	5
26	Percentage of Reactive Maintenance	decrease	Efficiency in coordination of maintenance process	1	10
27	Percentage of Reactive Maintenance	decrease	Probability to avoid collateral damages	2	5,5
28	Percentage of Reactive Maintenance	decrease	Probability to avoid total failures	3	6
29	Percentage of Reactive Maintenance	increase	Number of EM persons per shift	2	6,5
30	Percentage of Reactive Maintenance	increase	Percentage of new equipment invests	1	6
31	Percentage of Reactive Maintenance	decrease	Equipment lifespan	1	8
32	Percentage of Reactive Maintenance	decrease	Quality of monitoring	1	5
33	Percentage of Reactive Maintenance	decrease	Efficiency of spare part logistics	1	6
34	Percentage of Reactive Maintenance	decrease	Evenness of distribution of equipment downtimes	1	3
35	Percentage of Reactive Maintenance	increase	Percentage of rework	1	10
36	Percentage of Reactive Maintenance	decrease	Degree of exhausting wear limits	1	8
37	Percentage of Reactive Maintenance	increase	Duration of Machine Downtimes	2	8,5

A3 PdMSM Formulas for Dynamic Variables

Variable	Formula
Down_Percentage	UD_flow+SD_Percentage
Degree_Of_Exhausting_Wear_Limits	Number_Failures > 0 ? 1-Number_of_SparePartReplacements/Number_Failures : 0
MTTR	(Number_Failures > 0 ? RepairTime/Number_Failures : 0)
MTBF	(Number_Failures > 0 ? Uptime/(Number_Failures) : 0)
EQ_Availability	time() > 0 ? Uptime/time() : 0.8
MTOL	(Number_Failures > 0 ? UnscheduledDownTime/Number_Failures : 0)
Prob_Avoid_Downtime	Prob_Avoid_Downtime_Plan+(Prob_Avoid_Downtime_Plan*5.28*ImpactFactor*Predictive_Maintenance)
Equipment_Lifespan	Equipment_Lifespan_Planned - Equipment_Lifespan_Planned*8*ImpactFactor*Percentage_Of_Reactive_Maintenance

Percentage_Of_New_Equipment_Invests	Percentage_Of_New_Equipment_Invests_Planned +Percentage_Of_New_Equipment_Invests_Planned*6*ImpactFactor*Percentage_Of_Reactive_Maintenance
partnerAvailability_woWIP	getPSAvailability(1, processAvailability, EQ_Availability, Operator_Availabilty)
processingRateCurrent	processingRateMax*partnerAvailability_woWIP
processingRateMax	Nmbr_Runs_Weekly*BatchSize
Nmbr_Runs_Weekly	(1/RPT)*Nmbr_ProcessReleased_Machines*(1-noiseFactor)*expectedVolumePercentage
FF_focusOperation	CT_focusOperation/RPT
CT_focusOperation	FocusOperation/GR_focusOperation
GR_focusOperation	processedWafers/(time()*expectedVolumePercentage)
Degree_Tool_Dedication	1-Nmbr_ProcessReleased_Machines/Nmbr_Similar_Machines
WIP_Availability	limitMax(1,wafersToProcess/(partnerAvailability_woWIP*processingRateMax))
PS_Availability	getPSAvailability(WIP_Availability, processAvailability, EQ_Availability, Operator_Availabilty)
FourM_Synchronicity	Four_M_Synchronicity ? 1 : 0
percentageProcessInspections	percentageProcessInspections_Plan - percentageProcessInspections_Plan*3*ImpactFactor*processCapability
procCapability	processCapability
partnerAvailability_woEquipment_and_Operator	getPSAvailability(1, processAvailability, WIP_Availability, 1)
setupFrequency	1/(Number_SetupActions/time())
DegreeAutomation	DegreeAutomation_Plan +DegreeAutomation_Plan*8*ImpactFactor*processCapability
DegreeOperatorQualificationLevel	DegreeOperatorQualificationLevel_Plan-6*ImpactFactor*DegreeAutomation
Operator_Availabilty	limitMax(1, auxOperatorAvailability+auxOperatorAvailability*0.045*DegreeProductionStaffMotivation +auxOperatorAvailability*0.08*DegreeOperatorQualificationLevel)
DegreeProductionStaffMotivation	MotivatedOperators/Nmbr_Operator_OnShift
Nmbr_Operator_OnShift	UnmotivatedOperators+MotivatedOperators
auxOperatorAvailability	Nmbr_Operator_OnShift/required_nmbr_op_per_shift
Capa_Tool	GR_focusOperation*processAvailability*EQ_Availability*Nmbr_ProcessReleased_Machines
ProductiveTime	Uptime-StandbyTime
MTBA	Number_Assists > 0 ? ProductiveTime/Number_Assists : 0
Utilization	GR_focusOperation/Capa_Tool
percRepairTime	RepairTime/time()

EM_Availability	Nmbr_EM_OnShift/(requiredEM_Opt-requiredEM_Opt*8.6*ImpactFactor*Predictive_Maintenance)
Predictive_Maintenance	PM_Active
Degree_Of_Machine_Related_Process_Failures	percentageScrap*(percentageMRPF_Plan-percentageMRPF_Plan*8.4*ImpactFactor*Predictive_Maintenance)
percentageScrap	ScrapWafers/processedWafers
processedWafers	GoodWafers+ToReworkWafers+ScrapWafers
Yield	GoodWafers/processedWafers
percentageRework	ToReworkWafers/processedWafers
WIP_productionLine	PreProcess+FocusOperation+PostProcess
CT_productionLine	WIP_productionLine/GR_productionLine
FF_productionLine	CT_productionLine/RPT_product
GR_productionLine	(PreProcessFinishedStock+PostProcessFinishedStock+processedWafers)/time()
Efficiency_In_Coordination_Of_Maintenance_Process	EM_Default_Values(7) -10*ImpactFactor*(1+Percentage_Of_Reactive_Maintenance)*EM_Default_Values(7) +8.8*ImpactFactor*EM_Default_Values(7)*Predictive_Maintenance
Percentage_Of_Reactive_Maintenance	EM_Default_Values(6) -EM_Default_Values(6)*10*ImpactFactor*Predictive_Maintenance
Percentage_Of_Preventive_Maintenance	1-Percentage_Of_Reactive_Maintenance
Probability_To_Avoid_Collateral_Damages	EM_Default_Values(1) +5*ImpactFactor*(1+Percentage_Of_Preventive_Maintenance)*EM_Default_Values(1)
Probability_To_Avoid_Late_Effects	EM_Default_Values(4) +5*ImpactFactor*(1+Percentage_Of_Preventive_Maintenance)*EM_Default_Values(4)
Quality_Of_Planning_Procedures	EM_Default_Values(3) +5*ImpactFactor*(1+Percentage_Of_Preventive_Maintenance)*EM_Default_Values(3)
Speed_Of_Analysis	EM_Default_Values(3) +5*ImpactFactor*(1+Percentage_Of_Preventive_Maintenance)*EM_Default_Values(3)
Speed_Of_Reactions	EM_Default_Values(4) +5*ImpactFactor*(1+Percentage_Of_Preventive_Maintenance)*EM_Default_Values(4)
Degree_Of_Evenness_Of_Distribution_Of_Equipment_Downtimes	EM_Default_Values(2) -3*ImpactFactor*(1+Percentage_Of_Reactive_Maintenance)*EM_Default_Values(2)
Efficiency_Of_Spare_Part_Logistics	EM_Default_Values(3) -6*ImpactFactor*EM_Default_Values(3)*(1+Percentage_Of_Reactive_Maintenance)

	+6.4*ImpactFactor*EM_Default_Values(3)*Predictive_Maintenance
Quality_of_monitoring	EM_Default_Values(7) - 5*ImpactFactor*(1+Percentage_Of_Reactive_Maintenance)*EM_Default_Values(7)
synchronicity_EM_Availability	EM_Default_Values(6) +EM_Default_Values(6)*4*ImpactFactor*Predictive_Maintenance
uniBS	uniform(preProcBatchsize*0.9,preProcBatchsize*1.1)
uniCT	uniform(preProcCT*0.9,preProcCT*1.1)
WSPW	WSPW_Samples(round(time()))/7
actualTimeStep	getEngine().getNextStepTime()-time()
timeGrowth	Standby_flow+UD_flow+UP_flow
avg_NmbrEMOnShift	Nmbr_EM_OnShiftDS.getYMean()